

LEVERAGING AI IN HUMAN RESOURCE MANAGEMENT

ARTICLES FOR FACULTY MEMBERS

Title/Author	<p>AI for next generation computing: Emerging trends and future directions / Gill, S. S., Xu, M., Ottaviani, C., Patros, P., Bahsoon, R., Shaghaghi, A., Golec, M., Stankovski, V., Wu, H., Abraham, A., Singh, M., Mehta, H., Ghosh, S. K., Baker, T., Parlikad, A. K., Lutfiyya, H., Kanhere, S. S., Sakellariou, R., Dustdar, S., ... Uhlig, S.</p>
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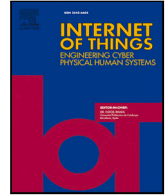
CLIMATE CHANGE AND SEA TURTLE NESTING

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Review article

AI for next generation computing: Emerging trends and future directions

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ABSTRACT

Autonomic computing investigates how systems can achieve (user) specified “control” outcomes on their own, without the intervention of a human operator. Autonomic computing fundamentals have been substantially influenced by those of control theory for closed and open-loop systems. In practice, complex systems may exhibit a number of concurrent and inter-dependent control loops. Despite research into autonomic models for managing computer

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Edge computing
 Serverless computing
 Quantum computing
 Machine learning

resources, ranging from individual resources (e.g., web servers) to a resource ensemble (e.g., multiple resources within a data centre), research into integrating Artificial Intelligence (AI) and Machine Learning (ML) to improve resource autonomy and performance at scale continues to be a fundamental challenge. The integration of AI/ML to achieve such autonomic and self-management of systems can be achieved at different levels of granularity, from full to human-in-the-loop automation. In this article, leading academics, researchers, practitioners, engineers, and scientists in the fields of cloud computing, AI/ML, and quantum computing join to discuss current research and potential future directions for these fields. Further, we discuss challenges and opportunities for leveraging AI and ML in next generation computing for emerging computing paradigms, including cloud, fog, edge, serverless and quantum computing environments.

1. Introduction

Autonomic Computing Initiative (ACI) from IBM was among the first industry-wide initiatives for the design of computer systems that require limited human interaction to achieve performance targets [1]. The Tivoli systems division at IBM focused initially at performance tuning of the DB2 database system using autonomic computing principles. The initiative was heavily inspired by observations from the functioning and coordination of the human nervous system and human cognition—i.e., the autonomic nervous system acts and reacts to stimuli independent of an individual’s conscious input; an autonomic computing environment functions with a high level of Artificial Intelligence (AI), while remaining invisible to users [2]. Additionally, a human nervous system achieves multiple outcomes concurrently and seamlessly (e.g., internal temperature changes, breathing rates fluctuate, and glands secrete hormones as a response to stimulus) adhering to pre-defined/evolved “limits” and norms, and acting on impulses sensed or learned from the body itself or the environment. As for the human body, an autonomic computing environment is expected to work in response to the data it collects, sensed or learned, without an individual directly controlling functions used to manage a system [3].

Autonomic computing – also referred to as self-adaptive systems – is a field of investigation that studies how systems can achieve *desirable* behaviours on their own [4]. It is common for these systems to be referred to as “self-***” systems, where “***” stands for the behaviour type [5], such as: self-configuration, self-optimisation, self-protection and self-healing [6].

An autonomic system’s capacity to adapt to environmental changes is referred to as “self-configuring” [7]. The system automatically upgrades missing or obsolete components depending on error messages/alerts generated by a monitoring system [8]. A self-optimising autonomic system is one that can enhance its own performance by successfully completing computational jobs submitted to it, reducing resource overload and under-utilisation [9]. Self-protection is an autonomic system’s capacity to defend itself against potential cyber-attacks and intrusions. The system should also be detecting and preventing harmful assaults on the autonomic coordinator managing the overall system [10]. Self-healing is a system’s ability to discover, evaluate and recover from errors on its own, without the need for human intervention [2]. By decreasing or eliminating the effect of errors on execution, this self-*** property improves performance through fault tolerance [11].

The ultimate vision is that neither self-managed systems nor self-healing systems need to be configured or updated manually [12]. In a broader sense, self-managed systems should be capable of controlling all of the aforementioned behaviours [13].

Different practical systems realise these outcomes to varying levels of granularity and success. Also, the level of human intervention and control can vary. As part of IBM’s Autonomic Computing paradigm, the Autonomic Manager (AM) is a smart entity that interacts with the environment via management interfaces (Sensors and Effectors) and performs actions based on the information received from sensors and rules established in a low-level knowledge base. The AM is set up by an administrator using high-level warnings and acts. Fig. 1 illustrates IBM’s autonomic approach in operation [1]. Initial monitors acquire sensor data for regular inspection of Quality of Service (QoS) metrics whilst engaging with external hardware and send this data to the next component for further evaluation. In the Analyse and Plan modules, data collected from the monitoring module is analysed and appropriate action plans are drawn up in response to system warnings. Using the results of the data analysis, this autonomic system takes appropriate actions in response to the generated warnings. After a thorough review, which includes verification and validation to provide guarantees that the adaptation will indeed work, the plan is put into action by the Executor, whose primary goal is to ensure that the QoS of an executing application is maintained. An Executor monitors changes in the knowledge base and acts based on the results of the analysis.

1.1. AI/ML for next generation computing: A vision

AI and ML can be used to support and develop autonomic behaviours based on data collected about systems operations. ML techniques, for example, can be used to discover patterns in the workload, where these patterns can be used to optimise resource management [14]. Additionally, to mitigate model uncertainty, ML-based dynamical system identification methods, such as recurrent neural networks, could be adaptively invoked by the autonomic manager to achieve self-learning. Thus, black- and grey-box models of the managed system can be generated during a concept drift and subsequently verified to check their sanity or even, detect mission-critical alterations of the system’s operation [15]. Further, AI may be employed in the analysis and planning stages of autonomic systems that are often arranged as monitor-analyse-plan and execute (MAPE) cycles [16], in addition to the use of

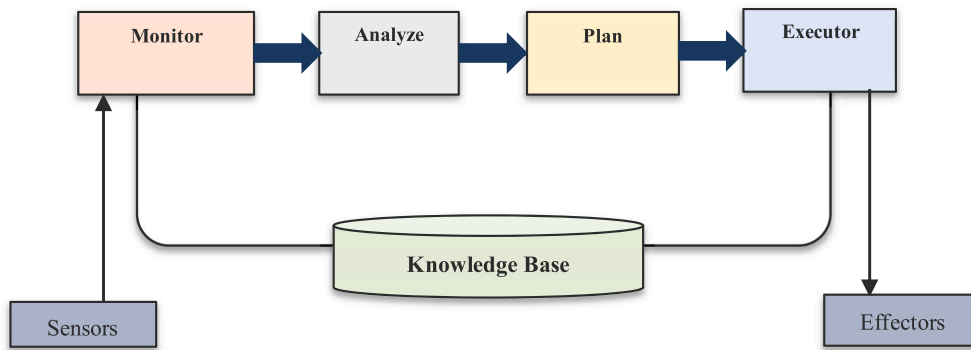


Fig. 1. MAPE-K loop for autonomic computing.

techniques from control theory. It is the combination of feedback control with data-driven model construction using ML that offers key benefits in support of autonomic self-management.

Among the notable types of autonomous computing solutions: feedback-based control is one common solution. The use of self-organising systems, such as particle swarm optimisation, cellular automata and genetic algorithms, are others. In the first category of solutions, systematic techniques for designing closed-loop systems capable of tracking system performance and altering control parameters are provided by autonomic computing [17]. There is a vast corpus of control theory literature and design tools that are used in these techniques. When it comes to the second type of solution, a variety of newly developing peer-to-peer approaches are now being employed to create massively scaled self-managing networks [18].

1.2. Motivation and aim

Autonomic computing has been integrated in computing paradigms such as cloud, fog, edge, serverless and quantum computing using AI/ML techniques [19]. The use of autonomic computing techniques is particularly significant when there is a large number of potential configuration options for a system. The greater the potential parameter space over which configuration options can vary, the greater the potential to optimise search over this space of possible options. Autonomic computing techniques are most useful *under the hood*, i.e. as a programmatic interface that can be invoked directly [20] from an application.

There are many applications that can manage node failures, network setup/updates and a limited ability to carry out performance optimisation on their own since most peer-to-peer networks are fundamentally autonomous. AI- and ML-based self-managing capabilities are becoming increasingly common in web services and data centre management software, allowing these systems to automatically adapt to shifting workloads [21]. However, autonomic features are not always included in schedulers and workflow managers, as such systems frequently lack the ability to monitor system condition and provide real-time feedback, making it difficult for these systems to be fully autonomous [22]. Integrating “tuning” capability that makes use of AI/ML techniques can extend the capability of such systems. For instance, self-managed computing platforms, such as Hadoop/MapReduce, provide self-healing and self-organising capabilities that enable the use of a large number of resources [23].

AI- and ML-based autonomic computing will become prevalent with increasing scale and interconnectivity of our systems, making manual administration and adaptation of such systems challenging and expensive. We expect AI- and ML-based autonomic computing will be the norm in the future—with human users still able to influence the behaviour of these systems through the use of judiciously integrated interfaces. Crucially, with the advent of cyberphysical systems and digital twins, quality-assured and mission-critical adaptations will become mandatory because the self-adaptive software will be responsible for physical assets, such as the unit operations of a processing plant.

But how should self-adaptive systems and AI/ML be combined? According to IBM, an autonomic system must meet the following eight criteria for computing systems using AI and ML techniques [2,8–10,24–27]:

- The resources that are available to the AI-powered system, as well as the capabilities and limits of the system, must be known by the system.
- As the computing environment changes, e.g., because of a concept drift, the system must be able to adapt and reconfigure autonomously.
- An efficient computer process requires a system that can maximise its performance via AI- and ML-based predictions.
- When an error occurs, the system should be able to fix itself or redirect processes away from the source of the issue.
- To ensure overall system security and integrity, the system must be able to detect, identify, and respond to numerous forms of threats automatically.
- As the environment changes, the system must be able to interact with and develop communication protocols with other systems.

Despite the system’s transparency, it must be able to predict demand on its resources, which can be forecasted with AI/ML techniques. Small, even inconspicuous computers will be able to communicate with each other across more linked networks, leading

Table 1

Comparison of our survey with other survey articles. ×:= method supports the property.

Works	1	2	3	4	5	6	7	8	9	10	11	Publication year
Varghese and Buyya [32]			×									2018
Abdulkareem et al. [33]		×		×								2019
Gill et al. [19]		×	×									2019
Massimo et al. [34]		×			×							2020
Li et al. [36]		×					×					2020
Kumar et al. [35]		×					×					2021
Hassan et al. [37]		×				×						2021
Our Survey (This Paper)	×	×	×	×	×	×	×	×	×	×	×	2022

Abbreviations: 1: Prospective Model, 2: AI, 3: Cloud Computing, 4: Fog Computing, 5: Edge Computing, 6: Serverless Computing, 7: Quantum Computing, 8: Explainable AI (XAI), 9: Risks and Benefits of AI-integrated Next Generation Computing, 10: Hype Cycle, and 11: Intelligent Edge.

to the notion of “The Internet of Everything (IoE)”, thanks in part to the emergence of ubiquitous computing and autonomic computing [28]. Crucially, AI-powered self-adaptive systems promise to cost-effectively and sustainably meet changing requirements in a changing environment and in the presence of uncertainty—vs., just adding more and more resources. Hence, in conjunction with the latest AI and ML techniques, autonomic computing is being studied and applied by a number of industry giants.

1.3. Benefits of AI/ML-integrated next generation computing

AI-based Autonomic computing’s primary advantage is lower total cost of ownership [29]. As a result, maintenance expenditures will be significantly reduced. There will also be a reduction in the number of people needed to maintain the systems. AI-powered automated IT systems will save deployment and maintenance costs, time, and boost IT system stability. Companies will be able to better manage their business using IT systems that can adopt and implement directives based on business strategy and can make alterations in response to changing surroundings, according to the higher-order advantages. Server consolidation is another benefit of using AI-based autonomic computing, since it reduces the cost and human labour required to maintain huge server farms [30]. Management of computer systems should be made easier using AI for autonomous computing. As a result, computing systems will be significantly improved. Another example of an application is server load distribution, which may be accomplished by distributing work across several servers [31]. Further, cost-effective and sustainable power supply policies can be accomplished by continuously monitoring the power supply.

As a consequence of AI, the following changes have occurred in autonomic computing:

- Cost-effective: Using computer systems instead of on-site data centres has its advantages. Despite the high initial costs, organisations may easily acquire AI technology via a monthly charge in the cloud. Systems using AI may analyse data without involving a human being.
- Autonomic: Enterprises may become more efficient, strategic, and insight-driven through the use of AI cloud computing. AI has the potential to boost productivity by automating tedious and repetitive tasks, as well as doing data analysis without the use of operator interaction.
- Data Organisation: Real-time personalisation, anomaly detection, and management scenario prediction may be achieved by integrating AI technology with Google Cloud Stream analytics.
- Making Intelligent Decisions: Intelligence-based data security is critical as more cloud-based apps are deployed. Network traffic tracing and analysis are made possible by AI-powered network security technologies. As soon as an abnormality is discovered, AI-powered systems can raise a red signal. Such strategy safeguards crucial information.

1.4. Related surveys and our contributions

As the area of computing continues to expand, there is a need for a fresh visionary work to review, upgrade and consolidate the current evidence and discuss potential trends and future perspectives in the field of computing. Varghese and Buyya [32] introduced an innovative survey on next generation cloud computing, which does not consider AI/ML. Abdulkareem et al. [33] presented a review on AI for fog computing only. Massimo et al. [34] explored literature for AI-based edge computing. Gill et al. [19] presented a review on AI for cloud computing. The surveys from Kumar et al. [35] and Li et al. [36] highlighted the potential role of AI in quantum computing. The suitability of AI for serverless computing is described in Hassan et al. [37].

By combining AI/ML with cloud, fog, edge, serverless, and quantum computing, we have created the first review of its kind. Adding to the previous surveys, this new research gives a new imaginative approach to assessing and identifying the most current research challenges. Table 1 compares our review with existing surveys based on different criteria.

1.4.1. Our focus

This paper leverages the expanding domain of Internet of Things (IoT), edge computing and the computing continuum as an exemplar application for AI-powered adaptation. There is a tremendous growth on applications that leverage such technologies, such as smart agriculture, environmental monitoring, industrial digital twins, smart cities, management of renewable energy generation/storage, etc. Nevertheless, our discussion can be expanded to other fields as well.

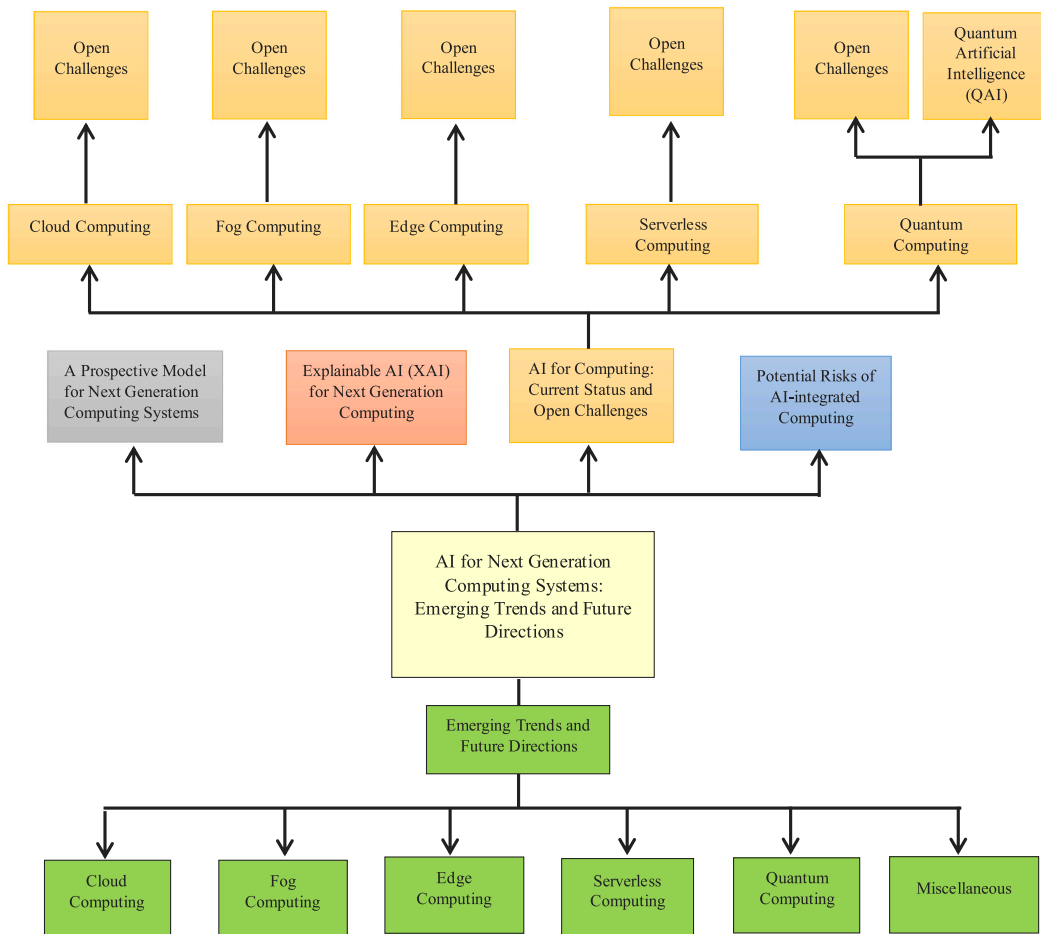


Fig. 2. The organisation of this survey.

1.5. Article organisation

The rest of this article is organised as illustrated in Fig. 2. Section 2 proposes a conceptual model. Section 3 is presents a vision and discusses various emerging trends in AI for cloud, fog, edge, serverless and quantum computing. Section 4 discusses the new research developments related to autonomic computing with embedded intelligence. Section 5 discusses the use of Explainable AI (XAI) for next-generation computing. Section 6 presents the potential risks of autonomic computing approaches that make use of AI/ML algorithms. Section 7 gives the hype cycle for autonomic computing and highlights the future directions. Section 8 concludes and summarises the paper.

2. A prospective model for next generation computing systems

To show the relationship between AI/ML and autonomous computing systems, we propose a prospective software architecture model as shown in Fig. 3. Our proposal integrates advanced technologies to offer effective computing services that fulfil the demand for a variety of IoT applications.

2.1. IoT applications

Gateway devices can be used by IoT/edge devices and end users to communicate with computer systems, abstracting away the interactions with sensors and actuators/effectors located on the edge [38]. The system can communicate with various and multiple instances of IoT applications (such as healthcare, smart city, farming, and weather monitoring) or their digital twins to efficiently provide AI and other autonomic services [39].

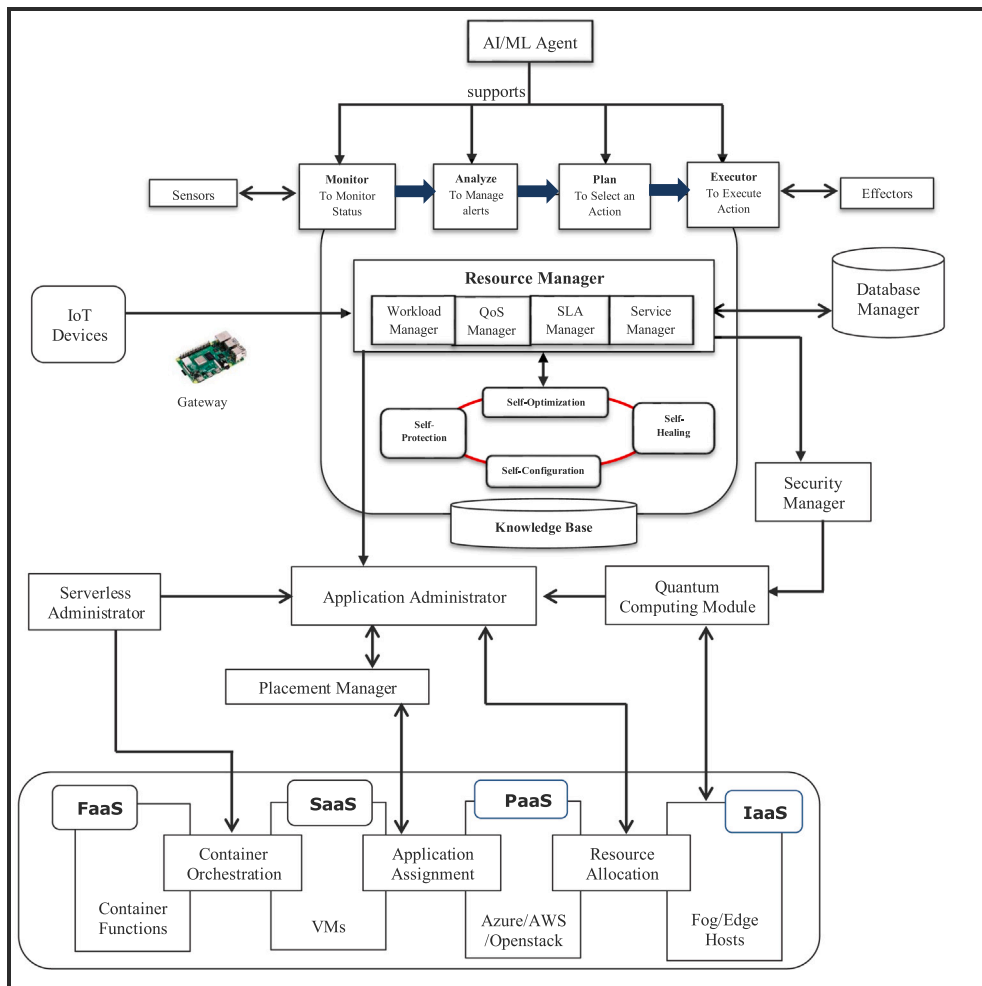


Fig. 3. A prospective model for AI-integrated next generation computing.

2.2. Resource manager

Distributed systems, including IoT edge platforms, require adaptive and fault-tolerant management of resources and scheduling of tasks. The proposed resource management module maintains the set of available and reserved resources (the number of CPUs utilised, the amount of memory, the price of resources, the kind of resources, and how many resources there are) as well as the desired resources, constraints (e.g., placement) and QoS per deployed task. Further, the module incorporates data supplied by the provider on the accessible and scheduled resources, as well as the resource specification (resource identity, resource category, configuration, data, use information, and pricing of resource).

When evaluating QoS, the QoS manager figures out how long it will take to complete a given workload. Priority queues (workloads with an urgent deadline in execution state) are created for critical cloud workloads based on Service Level Agreement (SLA) details, which includes details about the highest and lowest violation probability and penalty rate in the case of SLA violation. The service manager is responsible for overseeing all aspects of the system's operation. With the use of SLA and QoS information, a mapper may assign workloads to adequate resources, taking into consideration both SLA and QoS. After allocating the workloads to the available resources, the resource manager creates a workload schedule by predicting it using AI. In order to complete tasks within a certain budget and timeframe, the resource scheduler makes efficient use of the system's resources, which are predicted via AI/ML techniques. Finally, wherever possible, the resource manager will be providing explainable guarantees under uncertainty – potentially using explainable AI methods – that the proposed adaptation will indeed meet the desired QoS.

2.3. Autonomic model

This future model employs IBM's autonomic computing model [1], which emphasises self-healing, self-configuring, self-protecting, and self-optimising features.

- Self-healing is aimed at making all required modifications to recover from defects in order to keep the system running without interruption [27]. Software, network, and hardware errors must not impair the efficiency of the algorithm or workload regardless of their severity [10]. Any unintended exception in high resource-intensive applications can cause a software, hardware or network failure. AI-based systems can leverage a variety of data sources and sensor data to generate fault models and enable predictive – instead of reactive – fault detection and maintenance.
- The primary goal of self-protection is to keep the system secure from hostile purposeful acts by keeping track of suspicious activity and responding appropriately in order to keep the system running smoothly [9]. To prevent an attack, the system must be able to tell the difference between what is lawful and what is not. AI-based prediction systems can be used to achieve this: for instance, the system could be trained to detect vulnerabilities in the communications configurations/policies or identify code smells in the user-submitted functions/lambda.
- Installing missing or obsolete parts without requiring any human interaction is the primary goal of self-configuration. Depending on the situation, a developer may need to reinstall specific components or perform software upgrades [2]. Self-configuration takes care of the cost of resources and penalties for SLA violations, which can be predicted in advance through AI/ML.
- Dynamic scheduling approaches are used to match jobs and workloads to the best available resources in the self-optimising aspect [27]. The autonomic element's input is used to constantly enhance the system's performance through dynamic scheduling. AI/ML based adaptive scheduling can be used for data-intensive applications because it is flexible and can be adjusted to a changing environment with ease. Further, the impact of different QoS characteristics on system performance can be measured automatically [8].

Models for complex distributed systems that can self-heal, self-configure, self-optimise and self-protect have been developed using this idea. Autonomic elements (AEs) are primarily in charge of managing resources on their own [1]. Fig. 1 shows a schematic representation of the many components that make up an AE system. Interaction between all the AEs is necessary for the sharing of messages on system performance. AEs complete a necessary sub-task to maintain the system's performance based on interaction. There are four stages to the IBM model of an autonomic system [1]: Monitor, analyse, plan, and execute are the four steps in the process, which will be supported by AI/ML models to improve the monitoring, analysing, planning and execution. Further, AI-powered techniques could also improve the efficiency of the persistence (knowledge) component of the MAPE-K loop, especially in effectively resolving state synchronisation in a highly-distributed and potentially unreliable environment.

2.3.1. Sensors

Sensors gather data on the QoS metrics of the present state nodes' performance [2,8–10]. Input from computation elements is first sent to the manager, which subsequently sends this information to Monitors through the manager node. Faults (software, network, and hardware), fresh updates on component status (outdated or missing), and security threats are all included in the recent developments (intrusion detection rate).

2.3.2. Monitor

Initially monitors data from the resource manager node to continually check performance variances by contrasting AI-based predicted and real outcomes [2,8–10]. The threshold value of QoS metrics, which also contains the highest value of SLA violation, is already recorded in the knowledge base. The faults (network, software, and hardware), fresh upgrades of resources (obsolete or lost), security assaults, variation in QoS parameters, and SLA violations are noted, and this data is transmitted to the next module for more investigation. Each node has a QoS agent deployed to monitor and predict the performance of the above-mentioned QoS parameters for self-optimisation. Self-protection is achieved by installing security agents on all processing nodes, which are then utilised to track down both undiscovered and recognised attacks. After analysing the system's current database, additional abnormalities can be predicted using AI/ML. System invasions and system abuse are detected and classified as either normal or abnormal utilising its monitor and the system's attributes are compared with metadata. Hardening agents for software, networks, and hardware will be reducing attack surfaces by identifying corresponding flaws to achieve self-healing and self-protection. When a new node is introduced to the cloud, the hardware hardening agent scans the drivers and validates the replica of the original drivers. The new node is inserted when the device driver has verified it. This node will create a warning if it is still present in the system. The performance of the software and hardware components is monitored by agents for self-configuration. The software component agent retrieves the active component condition for all software components that are employed on separate processing nodes.

2.3.3. Analyse and plan

When the monitoring module sends data, the Analyse and Plan unit evaluates it and identifies a strategy for reacting to the alarm [2,8–10]. After a QoS agent generates an alert, the analysis unit begins predicting QoS metrics associated with a specific node. 'DOWN' status is reported for that unit, and the unit is restarted, and the state of that node is measured. Alternatively, new resources are added if the node state goes to 'ACTIVE'. After an alarm is sent by a hardware or software agent, the analysis unit begins examining the behaviour of the node's hardware and software (self-healing). Node 'N' should be set to "DOWN" if an alert is produced during workload execution and restarted, to measure the state of that node. The execution of the node's state switches to 'ACTIVE' if execution is continued, or alternatively another reliable node is chosen. Self-protection begins by examining attack logs once an alarm is produced by the security agent and a signature is created by the analysing component. After an alarm is issued by a

hardware or software component, the analysis unit begins studying the behaviour of a node's hardware and software components. It is necessary to designate a hardware component as "DOWN", reset the failed component, and then start it again in order to predict whether or not it is "CRITICAL" or "ERROR". Again when the data has been processed, this framework takes care of implementing the alert-related actions on its own.

Further, before any adaptation does take place, the modules will first provide evidence that the proposed plan will indeed complete successful. This is achieved using a combination of formal guarantees, which can be derived from the use of control theory. An AI-model can also be used to predict when the users might issue a goal update – based on external information or other types of operational data – and prepare/assess an adaptation plan ahead of time.

2.3.4. *Executor*

A plan is put into action by the executor [2,8–10], whose primary purpose in self-optimisation to enhance QoS and execute tasks within a pre-defined deadline. Using the data from the analyser, the executor may quickly, cheaply and efficiently add a new node to the pool of resources. If the resources are not already in the pool of available resources, then notify the user and negotiate a SLA before adding a new node from the backup pool of resources with the least amount of workload, price and power usage requirements. These aspects can be predicted in advance using AI/ML. A node that is not reliable should be replaced with a node that is the most stable amongst those available. To relaunch the node, the current status of a node is stored (checkpointed). The node is then restarted. If the problem persists, an alert is subsequently generated.

For self-healing, whenever a new component is introduced, it should be linked to other components and restarted.

2.3.5. *Effector*

New policies, regulations, and notifications are sent to other computing nodes via the effector [2,8–10], which serves as an interface between the various computing nodes. Through the effector, the computing nodes can work together to form a more powerful system. It is worthwhile mentioning that a system-of-systems approach is likely to be leveraged for such applications; hence, effectors of a top system might be triggering adaptation of a bottom system and so on.

2.3.6. *Knowledge base*

The main aspects of information stored in the knowledge base are the following: (a) The current and previous states of the system (including deployed applications, available computing resources, etc.), whose values are read via the system's monitors. (b) The desired state of the system, which is driven by specifications set by the user/admin/operator of the system; they include both functional requirements, such as the microservices network of deployed applications, as well as nonfunctional requirements, such as QoS Service Level Objectives (SLOs) on desired response time, tail latency, target resource utilisation, etc. (c) Current, past and predicted models – as well as meta models and surrogate models – of the system and its environment generated via AI/ML as well as the efficacy of the various AI/ML methods used for their training. (d) Current and past execution plans that are devised by the planner module and implemented by the executor module. (e) The actual code of the various interfaces the system provides to enable informed self-adaptation by autonomically incorporating improved methods for various operating aspects. For example, new AI/ML, scheduling and resource management algorithms, could be selected by the self-adaptation algorithm and added in, which would eliminate the need for the software engineering team to have to patch the system. (f) Further, the Knowledge Base will maintain pre-stored policies with predefined configurations to support system management. It is the responsibility of the system administrator to periodically update the policies stored in the Knowledge Base to reflect changes in resource scheduling regulations. A system admin will be replaced by an AI-based autonomic agent to handle the execution automatically.

Crucially, the knowledge module needs to provide a centralised location for the various running tasks, which could be executed as threads, processes and of course across multiple nodes of the distributed cluster, to safely store and exchange information. This kind of architecture is required for highly distributed systems; otherwise, direct communication between the various units will result in dramatic slowdowns due to locking and contention, increase the attack surface or even worse, into system failure due to synchronisation issues, such as race conditions, that can invalidate information manipulated by multiple actors. Finally, the knowledge base needs to be replicated, potentially across multiple reliability zones, to assure business continuity in cases of hardware and communication failures or even a catastrophe that knocks down a whole datacenter. As such, distributed consensus and adaptive data recovery algorithms are required to maintain data validity.

2.4. *Service management layer*

There is a database manager in this position (which manages the data of IoT applications effectively). AI-based systems can be used by Security Manager to predict and guard against external threats on task execution [40]. Application data may be securely sent during task execution with the help of a blockchain service. At runtime, the serverless manager controls the cloud resources that IoT applications are consuming. With the integration of Serverless data pipelines with quantum computers, efficient load balancing and dynamic provisioning may be achieved for the edge computing paradigm. It is the responsibility of the application manager to control the deployment of IoT applications and to provide data for the allocation of resources in advance, which can be achieved using AI/ML. The placement module serves as a bridge between the application manager and the application placement module.

Four categories of services are included at the bottom layer [40]: function (FaaS), software (SaaS), platform (PaaS), and infrastructure (IaaS). Function containers are used to provide a virtual environment for computer systems that can be dynamically scaled up and down. SaaS uses the notion of virtualization based on VMs to deliver cloud-based services. Platform as a service can

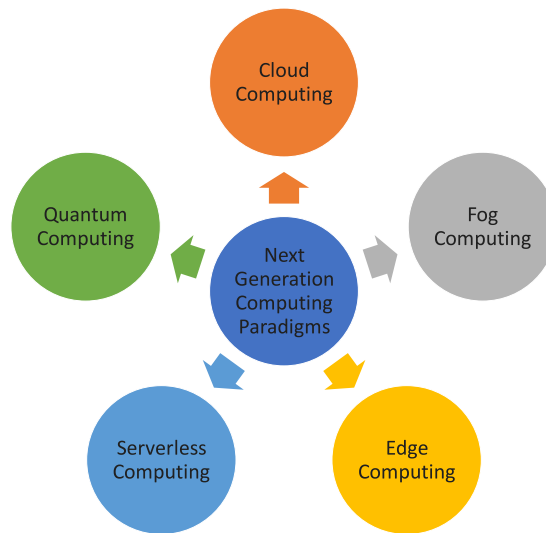


Fig. 4. Emerging computing paradigms.

be provided via Microsoft Azure, Amazon Web Service (AWS), or OpenStack. By lowering latency and reaction time at the edge devices, fog and edge computing may be used to deliver the infrastructure service. Orchestrating containers using orchestration is an intermediary step between deploying containers as a service and deploying them as software as a service (SaaS). The placement of IoT applications for dynamic provisioning and management is handled by application placement, which is a bridge between SaaS and PaaS. Machine learning and artificial intelligence-based approaches are used to schedule the cloud resources of PaaS and IaaS [41]. Using quantum technology, the system is able to perform nonce or Proof-of-work (PoW) computations in a fraction of the time.

3. AI for computing: Current status and open challenges

It is very important to identify the research opportunities for leveraging AI and ML in next generation computing for emerging computing paradigms, including cloud, fog, edge, serverless and quantum computing environments as shown in Fig. 4. This section discusses various new trends and open challenges in AI-integrated next generation computing.

3.1. Cloud computing

It is becoming increasingly evident that the rise of cloud computing and the rise of AI are mutually reinforcing. As a result, using AI in the cloud can improve the cloud's performance, efficiency, and digital transformation [42]. AI in the cloud computing environment is a crucial key to enabling organisations to become more efficient, strategic and insight-driven, while at the same time providing greater flexibility, agility and cost savings [43]. As a result, we turned to industry insiders for their insights about the expanding importance of AI in cloud computing.

AI and cloud computing may be combined in a variety of ways to enhance cloud computing. AI tools and software are synched with the power of cloud computing in order to provide an enhanced value to the existing cloud computing environments [44]. This combination makes enterprises efficient, strategic, and insightful. Data and applications hosted on the cloud allow businesses to be more responsive and adaptable, while also saving money for the company as a whole [44]. Existing capabilities gain intelligence, and customers receive an excellent experience, thanks to the addition of this additional layer of AI that aids in the generation of insights from data [44]. As a result, businesses may profit from a tremendously distinctive mix. Cloud is like a video game, which emits an enormous quantity of operating data and telemetry, much like a Tesla electric vehicle [45]. As a result, AI-based cloud computing is basically AI Ops, which uses algorithms to make sense of all this data rather than relying on humans [46,47]. In the post-COVID future, cloud-computing investment increased by 37 percent to \$29 billion in the first quarter of 2020 compared to the first quarter of 2019 [48]. Integrating AI and cloud computing can therefore help businesses get closer to their consumers while also increasing their operational efficiency [49].

Cloud computing environments and solutions are helping businesses to become more agile, adaptable, and cost-effective because this significantly cuts infrastructure administration expenses for corporations [50]. As a way to handle enormous data repositories, simplify data, improve workflows, and create real-time insights for day-to-day operations, AI gives companies more freedom. The operational weight may be shifted from processes and people to engineering and data [51]. That is why AI is boosting cloud computing in a variety of ways. The Software as a Service (SaaS) paradigm is currently being used to successfully employ cloud-based AI [52]. SaaS companies are incorporating AI into their solutions, which provides clients and end-users with enhanced capabilities.

Another method businesses are adopting AI to enhance their present cloud infrastructure is through AI as a service [53]. The use of AI makes applications more flexible and efficient, reducing mistakes and increasing production.

The cloud native paradigm derived from cloud computing has shifted the traditional monolithic cloud application into lightweight, loose-coupled and fine-grained microservices [54]. This paradigm can support the applications to be updated in a much more efficient manner. However, due to the increased number and time-sensitive features of microservices, their efficient management can be challenging. AI/ML based solutions can address some of the challenges, for instance, neural network based approach can be applied to predict workloads of microservices, and ML based techniques can be utilised to analyse the dependency of microservices.

The following are various advantages to deploying AI in the cloud:

- **Enhanced data management:** Data is king in today's data-driven world, which necessitates better ways to handle it. An enterprise's ability to keep track of that data is a major hurdle [55]. Cloud-based AI tools and apps that recognise, update, catalogue, and provide real-time data insights to clients. AI techniques may also be used to detect fraudulent activity and identify anomalous system trends [56]. Banks and other financial institutions rely heavily on this technology to remain competitive and safe in today's high-risk climate.
- **Automation:** Intelligent automation can now be implemented throughout a whole business thanks to the combination of AI and the cloud, which removes the last remaining roadblocks [57]. Predictiveness is enhanced by AI since algorithmic models draw on historical data and other patterns to deliver in-the-moment insights [58]. AI and cloud computing solutions can help businesses go from semi-structured to unstructured documents cognitively automated while also pushing the frontiers of effective infrastructure management, resulting in little downtime and impact [59]. As a result, the cost of doing business is transformed, and the customer experience is transformed as well.
- **Cost Savings:** Cloud computing allows businesses to just pay for the resources they utilise. This saves a significant amount of money compared to the typical infrastructure expenditures of building and maintaining massive data centres [60]. Saved money may be utilised to build more strategic AI tools and accelerators, which can then be used to increase revenue and save the company money at the core [61]. This will lead to better operational quality and cheaper expenses.

3.1.1. Open challenges

The following issues that may arise when these two technologies are combined:

- **Integration:** It is never easy to get started with a seamless integration of two different technologies. In order to accomplish this integration, companies must first move all of their apps and technologies to the cloud [57]. This is no small feat for many companies. Businesses may only begin to consider cloud-based AI after undergoing such a seismic shift. Thus, the technological sync is excessively reliant on companies that are implementing tangible digital transformations of their systems.
- **Inadequate data:** Large datasets with high-quality data are ideal for AI technologies. Businesses must make sure that their data is both accessible and clean in order for AI to be of any use [62]. Because data is often unorganised or missing, this is a big difficulty. It is critical that the solution's value be derived from high-quality data.
- **Security and privacy issues:** To prevent data breaches, businesses must be vigilant about protecting their sensitive and financial information from adversaries, who are likely to target them [63].

This synchronisation of AI with the cloud necessitates tremendous knowledge, resources, and financial investment if it is to be worthwhile for businesses. It is only when cloud computing and AI systems are properly integrated that companies will be able to utilise a wide range of powerful machine learning capabilities, such as image recognition and natural language processing [64,65]. As a result, additional businesses will follow suit in the future. Businesses will require an AI cloud in order to keep up with the rapid advancements in cloud computing. After successful implementation of it, AI operations will eventually become the standard approach for cloud management [47]. The cloud is already a powerful technology, but they believe that AI will make it even more so. With this combination, data analysis and management will undergo a radical shift. The marriage of AI with the cloud is a game-changer and will bring unparalleled value to end-users in a world flooded with vast volumes of data [62]. Now that cloud computing and AI are more widely available, they are producing upheaval in a wide range of industries throughout the globe. It is clear that technology has moved from being merely operational to one of strategic importance. AI is expected to help the company tackle new and more visible challenges, as well as open up a new universe for its potential clients.

3.2. Fog computing

Fog computing was established to supplement cloud computing services because of the rising use of the IoT and the necessity to handle and store massive amounts of produced data [66]. IoT applications with minimal reaction time requirements can be supported by fog computing, which provides basic network services [67]. It is difficult to distribute IoT application activities efficiently inside fog nodes in order to fulfil QoS and quality of experience (QoE) restrictions due to fogs' scattered, heterogeneous, and restricted resource nature [68]. Vehicle-to-Everything (V2X), health monitoring and industrial automation employ fog computing because it provides computing capabilities near to the user to meet reaction time expectations for these applications [69]. As a result, these apps create enormous amounts of information from the widespread use of IoT devices. Because of delays in long-distance data transmission and network congestion, cloud computing is unable to meet latency requirements [66]. It provides a network of gateways, routers, and compute nodes between the source of data and cloud computing centres. Because of the low latency and energy efficiency, as well as the reduction in bandwidth required for data transport, fog computing extends cloud computing [70]. Fog nodes can

be used to process sensitive data instead of sending it to the cloud, which improves security [71]. Using the data generated from various IoT devices, these applications aim to provide helpful information while also addressing latency concerns [67]. In recent years, researchers have increasingly turned to AI to help them analyse large amounts of data for the aforementioned uses. AI's Machine Learning (ML) and Deep Learning (DL) subfields give useful data insights and decision help [72,73]. Following that, we are discussing some of the AI-enabled fog computing technologies that make these applications possible.

For the IoT, 5G signifies more than just a new era of wireless innovation. More than trillions of sensors, gadgets, and machines are powered by AI and run autonomously from the data centre to the edge of the network [72,73]. In terms of speeding up data analysis and decision making, fog computing and edge computing are the two best technologies. Many "fog devices" will be networked and co-located as part of a distributed computing system known as fog computing [66]. Edge management, data collection, monitoring, analytics, and streaming all take place at the edge of the network in the fog computing nodes [74]. While fog computing is capable of connecting a limited number of devices, this technology has a far greater capability to handle real-time requests and to aggregate data from a much larger number of sources. Input-response delay is therefore greatly reduced. We have been able to access resources of all types, have scalable architectures with the press of a button, and utilise them from anywhere since Amazon's cloud was launched in 2006 [75]. Cisco claimed in 2008 that IoT, is the one of the technologies that will benefit from the cloud, but its roots date back to 1999 [76]. For example, we can save sensor data and act on it, automate processes using AI, and react in real time to circumstances that previously necessitated direct involvement. When IoT was first introduced, it promised to extend to both professional and personal areas, and how sensorization and communication protocols had to change to meet these new demands [77]. New paradigms have emerged as a result of the integration of sensor data and the application of AI to it. New terms like "Smart home" are being used to describe new technologies that make it easier and more convenient to manage our homes' energy use and other aspects of our daily lives [78]. On a broader scale, the term "Smart City" is used to describe cities, while "Smart Factory" is used to describe manufacturing and processing facilities. One thing they all have in common is the utilisation of data and automated decision-making in combination with automation, which can be easily achieved using AI and ML techniques.

An example of this is altering the configuration of a computer or railway, putting the brakes on an autonomous automobile, or sending a warning for a preventative maintenance. It is evident from the examples that decision-making and action-taking cannot be done on the cloud, but rather on devices that are closer to the sensors that collect the data. In contrast to cloud computing, fog computing offers a variety of advantages for IoT applications [79]. First and foremost, quicker and real-time processing are possible because local processing is used rather than relying on the cloud. As a result of the large number of IoT devices already in use and expected in the future, less network traffic means better communication. Additionally, more apps may be developed and operated everywhere there is an Internet connection. We need to think how AI could help in the automation?

3.2.1. Open challenges

Research on application deployment has already been done in several domains, such as industry and manufacturing, but there are still a number of issues that need to be addressed.

- Execution Time: For both service providers and customers, time is the most pressing issue. One of the key motivations for putting software in the fog is to speed up user reaction time. The time parameter was one of the performance indicators investigated in the literature [80,81]. When there are more demands, the QoS suffers. This difficulty has been partially alleviated by the presented techniques, but it remains a concern [82]. In the application placement problem, applied techniques for optimising time performance metrics in the category of deep learning algorithms [83–85]. We may be able to achieve better outcomes if we use different machine learning algorithms and evolutionary algorithms or novel combinatorial techniques.
- Mobility-awareness: Fog computing's lack of mobility support may be noticed when dealing with a large number of mobile users with varying application needs [86]. Consequently, migration methods and architectures that can handle a wide range of mobility activities are required. Migrating VMs or containers is something that has been discussed in a few publications [87]. Moving to a new location may be expensive, as well. Reinforcement learning (RL) approaches like Q-learning and State-Action-Reward-State-Action (SARSA) have been used to study this topic [88], but it remains a challenge in practical contexts where there are many requests [89,90].
- Resource Scheduling: Another problem the authors encounter is managing resources in a dynamic environment like fog, which has a limited amount of resources and a short reaction time for the user. The Fog environment is less flexible than the cloud when it comes to resource sharing [91]. Therefore, the issue of efficient resource utilisation must still be addressed. Resource allocation was based on a survey of existing research and the use of neural networks, support vector machines, and k-nearest neighbours (KNNs) [92].
- Energy-efficiency: The amount of energy used if supplied policies and algorithms are improved, idle fog nodes may be turned-off and energy consumption can be avoided in combination with QoS and QoE since the application modules are situated in the dispersed fog nodes [80,81]. Energy consumption and cost are influenced by memory, CPU, and bandwidth use which can be predicted using machine learning methods including K-means, KNNs, logistic regressions, branch and bounds and Deep Q-Network (DQN) and SARSA [93].
- Security and privacy: Fog infrastructure is critical to determining the security of the applications because of security concerns such as information degradation, identity disclosure, replay, and denial of service assaults [94]. Authentication, encryption, and data integration all need to be implemented in dynamic computing settings due to the lack of control that users have over their information [94].

- **Fault-tolerance and availability:** One of the primary reasons for the development of fog computing was to improve dependability. When it comes to fog computing, difficulties like sensor failure, a lack of access network coverage in a particular region or the entire network, service platform failure, and a broken user interface system connection are all part of the equation [72]. Another challenge in the fog environment is to increase the availability of apps. A heuristic approach to improving service availability and QoS is to map applications to fog communities and then transitively put their services on the fog devices' community, according to the service placement problem [66].

Images, video, natural language processing (NLP), and robotics are some of the more recent fog computing applications that are only starting to emerge [64,65]. Fog computing's picture placement and processing is one of the most widely utilised sectors of AI in research and industry, with the goal of differentiating objects or people from one another and the capacity to classify and discriminate photos based on image processing algorithms [95]. The use of fog computing for image processing-based applications decreases response time and improves QoS. Placement in fog settings with effective scheduling algorithms might be beneficial in circumstances linked to medical applications that demand precision in image processing and fast processing of medical data [33]. According to a literature, deep learning algorithms, such as Convolution Neural Networks (CNN) and Generative Adversarial Network (GAN), can be used in the image processing area in fog [96].

Another area of interest in the sector is NLP [96]. For sound processing and recognition, cloud and fog environments are needed to store data. For security reasons, deep learning approaches with sound imitation might be useful. For example, scenarios for smart homes and processing and identifying the homeowner's speech from outsiders should be done with care and speed, wherein effective scheduling methods for placement of NLP applications in fog will be proposed. Techniques from the field of deep learning may be beneficial here. Industry, trade, agriculture, and health all benefit greatly from robotics, making it an essential issue for discussion [33]. In circumstances when quick judgements must be made, the usage of fog environments that employ machine learning to process and make decisions, may be acceptable. In order for robots to communicate data, they require an environment like fog that responds quickly to their commands [97]. IoT defines each robot as an item capable of interacting with other IoT things and other robots [98]. Literature reported [97–99] that deep learning approaches for placement robot tasks in fog, however further research is needed. In the future, methods and scheduling algorithms for fog computing's application placement problem will need to be established depending on the types and categories of request applications, according to research and evaluations of literature [100]. An application placement issue in fog for robotics or simple image, video, audio processing is an example of this type of difficulty [101]. As a result, the QoS and QoE will be enhanced using AI.

3.3. Edge computing

Distributed computing has evolved from content delivery networks to become a generally accepted and commonly used edge computing paradigm that brings processing and data storage closer to the end user's location [102,103]. Instant data that is created by the user, and only for the user, requires compute and storage on the edge, but big data always requires cloud-based storage [104]. As customers spend more time on mobile devices, businesses have recognised they need to move key computation to the device in order to service more customers. The edge computing market has a chance to develop as a result of this. By the year 2023, it is expected to reach \$1.12 trillion [105]. 74 percent of all data will need to be handled on the edge by 2022, according to Gartner, compared to 91 percent of all data currently being processed in centralised systems [105].

Customers are more concerned about their privacy and want to know how and where their data is acquired and maintained. After completing the app's authentication procedure, a slew of businesses serve their clients by offering applications with AI-enabled tailored features [106]. These aid users in protecting their personal information. Customers often utilise speakers, phones, tablets, and robots to access AI-enabled gadgets [107]. Multiple levels of encryption and a dynamic encryption process are required due to the sensitive and personal nature of the data. Edge nodes facilitate the construction of a highly distributed architecture and help establish the appropriate security strategy for each device [108]. There are worries about latency when data is sent across networks and devices since services are dispersed at both the network and device levels. Due to this delay, the work must be done on the fly. Having several endpoints of load balancing is a need when an application has to be end-to-end resilient and have a widely spread architecture. Resiliency at the device level is increased by the fact that data computing services are closer to the mobile device or on the edge (referred to as a "cloudlet") [109]. We have to think, how these challenges can be overcome using AI?

Edge computing is a major enabler for AI, giving high-quality performance at a low cost. This is the best way to understand the link between AI and edge computing. We can benefit from the marriage of AI with cutting-edge computers [110]. Edge Computing helps AI-enabled applications overcome the technical problems of AI-enabled applications because of the data- and compute-intensive nature of AI. AI and machine learning systems absorb vast volumes of data to spot patterns and deliver reliable suggestions [111]. Cloud-based streaming of high-definition video data results in latency issues and increased costs, since huge bandwidth is utilised, in AI use cases requiring video analysis [84]. When ML triggers, decisions and actions must be made in real time, the latency and dependence on central processing in the cloud are detrimental. Processing and decision making may be done at the source of data, which means that actions can be taken at the edge and backhaul expenses can be avoided, making the edge an ideal location for data processing [112]. Rather of storing sensitive data on the cloud, the edge stores client location data. Streaming data to the cloud only includes the most important information and datasets, leaving the rest of the data behind [113].

Due to their scattered and complicated nature, edge computing networks have brought several issues when it comes to infrastructure management. There are a number of activities that must be completed in order to effectively manage resources. These include workload estimation and task scheduling as well as VM consolidation, resource optimisation, and energy conservation [114].

In dynamic, fast changing settings and in real-time scenarios, traditional pre-defined rules, largely based on operation research approaches, have been used for resource management in the past. AI-based technologies are increasingly being employed to address these concerns, particularly when decisions must be made. Approaches including AI, ML, and DL have become widespread in recent years. On the other hand, deciding where to carry out a work on the edge is a difficult choice that takes into account aspects such as the amount of traffic on edge servers and the mobility of users [115]. In order to further on the element of user mobility, the cache must be able to forecast where the user will go. For the sake of reducing expenses and energy consumption, it is located at an appropriate edge server. Reinforcement learning, neural network models, and genetic algorithms are some of the approaches that are employed [116].

In the commercial and industrial sectors, the advantages of Edge have quickly spread. Specifically, the reduction of IT equipment's growing expenditures on cloud and network bandwidth. All of the company's activities take place in different parts of the world. Only an estimated 1% of the monitoring data is relevant for business insights like anomaly identification or future event prediction, despite the fact that the cloud and big data centres are overflowing with data [117]. Edge delivers high-quality business services through local processing, analytics, and local devices. This is the operational efficiency and significance of the edge, since it prevents the transfer of terabytes of unnecessary data to the cloud/data centres and only communicates pertinent actionable data to the end user [118]. Every day, new and creative applications for edge's capabilities emerge. Edge computing still has a problem in moving to the last-mile of dispersed networks, but new use cases in industrial applications show a strong convergence with AI in particular, offering substantial value to businesses [119]. In the automotive, construction, process, and manufacturing industries, augmented reality, virtual reality, and mixed reality are becoming increasingly popular [118]. This necessitates a scalable, highly adaptable, and quick-to-respond computing infrastructure that is always available. Provides a low-latency experience and application instances that are near to the end user AI and machine learning have a plethora of uses in Edge Computing. NLP and CNN are two developing technologies that are used in a wide range of everyday applications [96]. Smart retail, contact centres, security, and legal assistantship all benefit from NLP's ability to parse human voice, recognise handwriting and classify text. Use cases such as quality control, facial identification, healthcare, and industrial safety can benefit from CNN capabilities in visualisation algorithms, which enable to detect faces and other visual data [96].

3.3.1. Open challenges

As compared to cloud, fog, or serverless computing, the problems of edge computing environments are markedly different. As a result, the edge environment is plagued by issues related to scalability and performance, especially when dealing with mission-critical data and applications [111]. It is tough to keep track of the health and state of each IT component, especially when there are so many remote edge locations to keep track of, much alone visualise and analyse their influence on other linked equipment, when considering the scale issue [120]. Highly dispersed and diverse networks define edge settings. Because of the disparate nature of the infrastructure's components and the high costs associated with acquiring the various skills and resources required, this creates "edge silos", which only serves to complicate matters further [84]. To handle the extremely dispersed and heterogeneous edge environment, AI-based intelligent software is crucial. It helps to collect and unify data from many sources and provides a highly abstracted "low touch" monitoring and administration, which eliminates human involvement. It is also possible to have entire client security without the client's involvement thanks to automated security and responses. You may pick from a variety of suppliers, avoiding vendor "lock-in", and switch out equipment with no negative impact on your business or cutting-edge efficiency [112].

Additionally, real-time performance management between end points, such as consumers and cloud/data centres, is a critical issue [113]. End-to-end views and data repositories at all sites are supported by technology tools that continually monitor performance metrics and data flow. For situations when edge equipment fails or is unavailable, edge infrastructure has built-in redundancy to isolate, repair and sustain acceptable levels of functioning [114]. If you run an edge data centre where multiple teams are in charge of different portions of the infrastructure, you will run into certain inefficiencies. Advanced correlation and analytics, based on AI, are quite helpful in this situation for examining, consolidating, and unifying data from many sources, transforming data into information, and communicating that information with the concerned roles in the team. Information that can be used to help automated processes is supplied [115].

The followings are the key open issues of adopting AI in edge computing:

- With tremendous advantages, edge computing has a number of challenges to overcome. Edge computing adoption is being stifled by some of the causes listed above. Edge computing has no legal, societal, or ethical framework for the use of AI. We need to do more study on the present benchmark tools and techniques. Newer technologies have a hard time being integrated into existing legacy industrial systems since they are not modular. Information security issues and a lack of integration testing with new entrants further limit technology use [116].
- Small and inexpensive, most edge devices do not require third-party API authentication, leaving them open to exploitation [104]. They are designed with simplicity of use and low cost in mind, not security in mind. Edge devices that gather personal information, such as email addresses, phone numbers, health information, and credit card data, are on the rise as a result of specialised apps [121]. The necessity for an AI based security framework before beginning large-scale and sensitive edge initiatives naturally causes IT and network administrators to be apprehensive [117].
- For AI-integrated edge workflows, new software frameworks and toolkits are needed [111]. Working with heterogeneous hardware and platforms, as well as the resources available in a workflow, will be supported by these software frameworks [96].

- When it comes to the administration of edge devices, there are no set standards and regulations that apply universally. The complexity of the IoT network architecture increases as more IoT devices are added to the edge [118]. There is still much to learn about the local consequences of IoT standards for different companies across different geographies, despite the fact that the US and UK governments have produced them. Organisations require a framework of regulations and criteria before they can make the decision to shift their data and application assets to AI-integrated edge computing environments, according to their perspective [115].
- Only by fully integrating edge computing into existing cloud architecture can its full potential be realised using AI, making edge computing the crucial missing connection between data sources (the devices) and cloud computing (core network) [107] because edge nodes have a limited storage and computing capacity [110].
- The main strength of this system is its tight interaction with the cloud. As more businesses move to a multi-cloud environment, it becomes more difficult for the cloud to set up a redundant AI-integrated edge network to accommodate incoming data traffic from numerous nodes [108]. High bandwidth needs and redundant data reporting and routing requirements for IT managers have increased the search for cloud suppliers capable of meeting these demands [111].
- Additionally, establishing an AI-integrated edge computing environment requires an initial investment in edge-enabled software frameworks and hardware [109]. The fact that this investment typically has to compete with other company objectives makes it a bottleneck. In developing countries, this problem is exacerbated.
- Many small and medium-sized businesses (SMEs), IT managers, and government decision-makers are unaware of the possibilities and applications of AI-integrated edge computing [84]. It may take some time for nations in Asia-Pacific that are still learning about cloud computing to adopt its capabilities for edge computing. Micro data centres, rather than edge workloads, are preferred by most service providers in emerging economies, as they are more cost-effective [112].
- With the arrival of 5G, billions of devices will be able to communicate with each other, and the network will see a rise in the rate at which connected devices are added and removed [105]. IT managers' judgement in implementing edge computing will always be questioned and adoption will never achieve its full potential without a standard, proven, and recognised edge monitoring technology [113].
- Faster R&D interventions and innovations in security, governance and standards/frameworks are the road to alleviate the difficulties for the adoption of AI-integrated edge computing [114].

Satellites in low-Earth orbit (LEO) are being built by private firms including SpaceX and Amazon to give worldwide broadband internet access [122]. It will be vital to determine if and how edge computing principles could be implemented in LEO satellite networks as the group of subscribers to such a access network increases.

3.4. Serverless computing

When it comes to designing cloud-native apps, serverless computing is becoming increasingly popular. Serverless is a cloud computing paradigm that abstracts away the management of operational aspects [123]. Because developers no longer have to worry about maintaining infrastructure, serverless computing is likely to expand considerably quicker [124]. Because of this, cloud service providers may more easily manage infrastructure and automated provisioning with serverless computing. The time and resources required for infrastructure management are also reduced as a result of [125]. It is the purpose of serverless computing to guarantee that the finest serverless technologies are used so that the investment is minimised and the return is highest [126]. Serverless computing and infrastructure are characterised by the following terms:

- Functions: Using event-driven models, serverless functions are implemented in serverless computing. Because the code is automatically executed as events occur, they are able to speed up the development process [127]. As a result, numerous services can be linked to the present application. Using these features, you may effectively create the pay-per-execution model [128]. It is billed for the time and resources used on executing code under this paradigm.
- Kubernetes: Developers have the option of bringing their own containers to Kubernetes through Serverless Kubernetes [129]. In Kubernetes-managed clusters, these containers may be automatically scaled up or scaled down. In order to deal with exceptional traffic situations and fluctuating workloads, this automatic scaling function is activated.
- Workflows: A low-code or no-code approach is used with serverless workflows [130]. It is an aim of this method to reduce the planning overheads associated with several activities at once. With these processes, developers may connect various cloud and on-premises services. Serverless computing has the capability to learn new APIs or standards, so interactions do not need to be coded [131].
- Application environments: Both the back-end and front-end of a serverless application environment are hosted on a dedicated server service. Fully-managed services via dedicated servers assume responsibility for the application's scalability, security, and compliance monitoring [132]. As a result, running an AI-based application on a serverless computing platform is significantly simpler, as serverless computing meets the dynamic scalability and security requirements of applications while still conforming to industry standards [133].
- API Gateway: An API gateway that is both centrally controlled and entirely managed is achievable with a serverless API gateway [37]. This application makes it feasible to administer, secure, and analyse APIs on a global scale. The management of authorisation and other services (such as content and user services) is therefore made simpler for a serverless API gateway. Serverless computing infrastructure enables automated API support using AI and database connectivity for every service that requires it, as stated previously [134].

Platforms across the board are embracing AI because it is the future of technology. We have been able to make better, faster judgements because of these AI-powered platforms. They have changed the way businesses do business, the way customers interact with them, and the way we gather and analyse business data. Complicated machine learning systems have a significant impact on the productivity and efficiency of developers [124]. A serverless design, on the other hand, addresses most of the issues that developers experience. Using a serverless architecture, the machine learning models are properly handled and the resources are effectively managed [135]. As a result of this design, developers may spend more time and resources working on AI model training rather than server infrastructure management.

Complex challenges typically need the development of machine learning systems. They analyse and preprocess data, train models, and fine-tune AI models, among other things. As a result, APIs should be able to run smoothly [136]. Serverless computing and AI should be used to ensure that data storage and message delivery are uninterrupted. Machine learning models may benefit greatly from serverless architecture, which offers a wide range of options and advantages [137]. Virtually little administration is required to run any form of application or back-end service. As incoming requests of any traffic volume come in, the infrastructure provider allocates its own computing execution power accurately.

AI/ML integrated serverless architecture will have following merits:

- Fair pricing: Serverless design makes execution-based pricing possible, so you only pay for services that are really being used [138]. As a result, the pricing model is more flexible and the cost is significantly reduced.
- Independent work: Serverless computing enables the development teams to operate autonomously with little intervention and delays. Models are viewed as distinct functions because of this. Invoking this function has no impact on the rest of the system and can be done at any time [37].
- Autoscaling: This feature frees up the developer to work on other projects while the system adjusts itself to the changing scope [139]. Storage prediction is no longer necessary when using autoscaling because developers may make changes on the fly.
- Pay-as-per-usage: Using a new model called “pay-per-use”, customers only pay for resources when they really use them. You do not pay for the amount of servers with serverless computing, but rather for the use of services [140]. Combined with the scale-to-zero feature of serverless, one just has to pay for the number of executions and the length of time resources are utilised for.
- Hassle-free server management: Serverless computing provides backend services that may be accessed only when they are needed, freeing users from the burden of managing servers [141]. A serverless service eliminates the need for the user to be concerned with the infrastructure that underpins the service. With serverless backends, service providers do not have to modify their setups if they want to raise or reduce the amount of bandwidth they are reserving or paying for [139]. It was difficult and expensive for web developers to own the hardware necessary to run a server before the introduction of the Internet.
- High availability: Serverless programmes have become more popular due to their built-in availability and fault tolerance. No need to construct services that will deliver these features to your application, therefore you do not have to. Your company does not need to invest in new capabilities because they are constantly available [142].

By reinventing automation and enhancing the corporate environment, AI has taken over today’s life and made it easier. Machine learning algorithms on serverless architecture may be used in a variety of ways to make jobs easier and data more accurate [139]:

- Applications that employ GPS gather user data, such as their location and their purchasing habits, to provide suggestions about their preferences or the next thing they should buy. AI assesses the frequency of alerts and suggests a number of options that the app users may be able to bear and enjoy before turning off the notifications. Using this method ensures that clients find the material useful and enriches the user experience [140].
- Using AI models, it is possible to examine a customer’s financial viability before recommending an increase in purchasing power. Prior to requesting any further information, the system will run a credit check to determine their creditworthiness. As soon as all of the prior invoices have been paid, the system decides if the transaction should go through or be put on hold.
- As part of logistics, it is important to keep an eye on the routes and determine how traffic overloads influence customers. In order to help businesses make better decisions and enhance customer service, AI analyses the routes and proposes alternate routes [136].

3.4.1. Open challenges

The following is a quick description of the open issues and challenges that serverless computing presents for AI applications:

- Vendor locking: If a company has committed to a cloud-based provider that provides technological implementation, switching suppliers will be difficult. The lack of industry-wide standards is responsible for around half of the challenges to cloud computing adoption [143]. To understand the consequences of vendor lock-in, no amount of investigation or study can be relied upon. Those who fail to keep an eye out for traps end up falling prey to them. In addition, a serverless interface must be carefully monitored because of the multiple risks it presents [144].
- Switching vendors: Lock-in circumstances can be seen in two different ways, depending on who is looking at the event. In their opinion, the problem with serverless computing today is not the programme itself. Another contributing cause is serverless computing, a new and fragmented technology that now has a younger audience that is overly reliant on it [145]. Businesses should only agree to a platform after conducting comprehensive research and receiving multiple offers from rival service providers. A single cloud may be all you need instead of hurrying to implement a slew of different ones.

- Less transparency: As the backend infrastructure is handled by an outside company, there is less transparency about how things actually function. The programme's inner workings may be obscured, especially if it interacts with other applications. Here are a few examples of how this may be put to good use: The security measures associated with an external PaaS service connected to your application, for example, are generally not well known [146].
- Others are in-charge of infrastructure management: Because our infrastructure is in the hands of a third party, it is more difficult to have a comprehensive understanding of the entire system. Using end-user-targeted devices under this paradigm, infrastructure is under the control of another firm, malware can nonetheless infiltrate your environment [147].
- Sustainability: An increasing amount of data generated on the edge is being submitted to the cloud for ML training/inference; the overall transmission energy is around 30% of the total energy requirements of datacenters globally and rising fast. Research is required to ensure the upcoming serverless paradigm is sustainable with a focus on power-off techniques, increased computational density via smart workload consolidation, submitting the kilobytes-long function to the data vs., submitting terabytes of data to the function, and effectively combining serverless edge resources for multitenant clients—e.g., by sharing artificial neural network layers with an acceptable tradeoff in accuracy [148].

AI has revolutionised market research and customer behaviour. Customers' preferences are recorded and analysed by an AI model, which then shows their customised content. Serverless computing simplifies the AI development process by removing the need for a dedicated server. As a result, serverless architecture entails handing over the management and monitoring of the infrastructure to a third party. That is why it is a good idea to work with a reputable cloud service provider. To guarantee that the infrastructure works smoothly, the cloud provider must have handled multiple comparable projects and have expertise in hosting and handling AI/machine learning and serverless architectures.

3.5. Quantum computing

Quantum computing promise is to be the one technology that has the potential to fundamentally alter AI. This section introduces the capabilities of quantum computing and its potential influences on AI and the economy [149]. The consequences of this approach to computation could affect a considerable range of aspect of intellectual and economic activities on our societies. With the enormous influence is AI having, all across the world, the combination with Quantum computing may have a multiplier effect to trigger a revolutionary effect on AI.

Quantum computing utilises a novel approach to data and information processing: Information, encoded in the quantum states of quantum systems, is processed accordingly to the law of quantum mechanics opening up some opportunities that are not available to the classical way of processing information. For example, quantum superposition and quantum entanglement [150]. Quantum entangled is the property of quantum systems of limiting the amount of information an observer may obtain on parts of a global quantum state, making it impossible to provide a complete description from the knowledge of only the component states. The term "superposition" refers to the possibility of *combining quantum state* in order to produce another valid quantum state.

Previous features of quantum systems trigger, from one side, the power of quantum computing (if sufficiently shielded from interactions with environment), but represent also the main limitations that do not allow an efficient simulation of quantum systems by present computer systems, even AI-powered supercomputers. In fact, the scaling of the phase space within which composite quantum systems evolve grows exponentially with the number of component systems.

The unit of information used by Quantum computers is the qubit, which replaces the bit used in classical computers. The state of a qubit $|\psi\rangle$, which could be an atom, a photon, a circuit, etc., can be represented, mathematically, as a vector in the complex Hilbert space [150], with two mutually orthogonal basis states $\{|0\rangle, |1\rangle\}$, as follows

$$|\psi\rangle = a|0\rangle + b|1\rangle, \quad (1)$$

where $|a|^2 + |b|^2 = 1$, and $a, b \in \mathbb{C}$ are Complex numbers. The exploitation of quantum superposition (See Eq. (1)), and quantum entanglement is what makes quantum computing considerably more powerful for certain tasks than classical counterpart [150].

The simulation of quantum systems has been the original scope motivating the endeavour to build a quantum computer [151], but it has only been after the discovery of quantum algorithms able to achieve practical goals that the interest in building this devices started to attract increasing attention. After the seminal works to formalise the concept of quantum computer [152], several algorithms followed that allowed to achieve tasks that were considered hard for classical computers. The discovery of the Shor's algorithm [153] provided an efficient solution for factoring large numbers, that had critical implications for crypto-analysis, boosting studies in both quantum computation and quantum cryptography. Running effectively the Shor algorithm on a working quantum hardware, however, it would require a level of accuracy in implementing register initialisation, quantum operations on multiple qubits, and storage of quantum states that are not yet achieved by current state-of-the-art devices [154]. It is also worth to mention that quantum computers have their own limitations. For example, it is not expected that they can efficiently solve NP-hard optimisation problems [155] and, coming to searching, the speed-up offered by quantum computers scales quadratically with respect to the time needed by a classical computer (Grover's algorithm [156]).

Building a quantum computer is, in fact, not an easy task: as experimentalists know pretty well, the advantages of quantum computing, offered by features like quantum superposition and entanglement, tend to vanish exponentially faster with the size and complexity (i.e., the number of quantum systems involved) of the hardware. Nevertheless, in recent years, we have seen a spectacular increase in the interest of major high-tech players (IBM, Microsoft, Google, Amazon, Intel, Honeywell), and a flourishing of many young companies aiming at proposing solutions for quantum computing, with various core technologies employed, ranging from

superconducting devices [154], to trapped ions [157], to integrated light circuits [158]. These are just some of the many companies that are today financing quantum initiatives and are interested in developing this technology. Despite the difficult challenges ahead, Google AI group has made significant progress during the recent years [154], achieving what is known as quantum advantage building a programmable quantum computer, named Sycamore. Similarly, IBM has recently announced the first quantum computer to pack more than 100 qubits in their hardware, *Eagle* chip [159], representing only a first step of busy research and engineering programme during which the tech-giant is planning to push figures to more than 1000 qubits by 2023. However, as said, the challenges to preserve the delicate features of composite quantum states rely on the ability to shield these devices from the external environment to allow coherent quantum evolution to take place under the presence of even very small amount of noise. For this reason these devices need ultra-low temperature of fractions of Kelvin, which pose challenges also for designing the appropriate materials able to perform well at such low temperatures.

3.5.1. Open challenges

While universal quantum computers remain the long term challenge of quantum computing, Noisy intermediate-Scale Quantum (NISQ) devices are a foreseeable target to achieve in the forthcoming years. With such devices physicist may start to effectively simulate complex composite quantum systems, and should be able to study exotic quantum states that have not been accessible in physics laboratory yet.

For the next step, once NISQ devices will be reliable and well developed, we will need to overcome the limitations imposed by the presence of noise during computation, by supporting the main computing unit with effective quantum error correction (QEC) circuitry. That may open road towards fault-tolerant quantum computation that will need to involve thousands and more qubits. In fact, QEC requires a considerable cost in terms of the number of qubits and logic gates to be implemented. The road towards the implementation of complex operations like those needed by the Shor factoring algorithm is still long but while the research is focused on improving the performance of quantum devices and the optimisation of quantum operations, numerous entrepreneurs are also interested in producing quantum software solutions. Consequently, many investors are expected to invest in start-up companies that are revolving around quantum computing technologies, and in perspective the interest in quantum computing is likely to increase.

Pharmaceutical investors' interest in quantum computing has sparked. Many sectors can benefit from quantum computers and commercial solutions. The financial industry, healthcare, genetics, pharmacology, transportation, sustainability, and cybersecurity are all direct beneficiaries of quantum computing [160]. Quantum computing's potential has been picked up by the banking industry. Financial analysts frequently make use of quantum computational models that incorporate probabilities and assumptions about how markets and portfolios operate. To do this, quantum computers might help by processing data faster, running better foresight models, and balancing conflicting options more accurately. They might also assist in the resolution of complex optimisation problems, such as portfolio risk optimisation and fraud detection [161].

Quantum algorithms in IBM's Cloud Computing platforms outperform classical Monte Carlo simulations, according to a research the company just presented. There is a lot of potential for the healthcare business to profit from quantum solutions. Quantum computing might lead to improved approaches to personalised medicine by allowing quicker genomic analysis to create personalised treatment strategies specific to each patient [162]. Genealogy research generates a lot of data. As a result, analysing DNA information requires a significant amount of processing power [163]. Currently, companies are reducing the costs and resources needed to sequence the human genome; but, a powerful quantum computer might sift through this data considerably faster, making genome sequencing more efficient and scalable [164].

Another area where drug development might benefit from quantum computing is in the field of protein folding [165]. This might help speed up drug discovery efforts by making it easier to predict the effects of pharmacological compounds [166].

A crucial aspect where quantum computers, and the promise to build one, have had considerable impact is in the field of security and cryptography. Public-key cryptosystems are the foundation of today's era of communication. Rivest–Shamir–Adleman (RSA) encryption is in fact the most common cryptosystems for securing transmission of data over networks, and its working mechanism and security requires factoring large prime numbers, beyond the capabilities of current classical computing limits. However, as mentioned above, quantum computing capabilities, exploiting Shor's factoring algorithm may renders such encryption models obsolete. This has led to increasing research, and investment, over the last decades to build safe cryptosystems in a quantum computing era, and the projections for the next years show this interest to grow, e.g., Toshiba's quantum cryptography revenue target is \$3 billion by 2030 [167]. In the meantime, while the efforts to design and implement effective quantum-key distribution (QKD) protocols expand, the National Institute of Standards and Technology (NIST) has also issued recommendations for post-quantum cryptography standards [168]. It has begun a process to request, assess, and standardise one or more public-key cryptography algorithms that are resistant to eavesdropping performed by quantum hardware.

Quantum computers have also been proposed for environmental applications, in the hope that quantum computing may open up new avenues for dealing with climate crises, identifying and optimising process that may help cope with global warming and other climate change effects [169].

3.5.2. Quantum Artificial Intelligence (QAI)

Quantum computing is more effective than classical computing in managing large amounts of data. A quantum algorithm is a mathematical algorithm that executes on a realistic model of quantum computation; the quantum circuitry of computation is the most often used model. The state of a quantum computing system can be seen as the information encoded in the physical quantum state supporting the specific implementation. Quantum information theory is based on these fundamental object, quantum bits (the unit of information), quantum gates (the devices that operates on quantum bits), and quantum channels that connect gates and

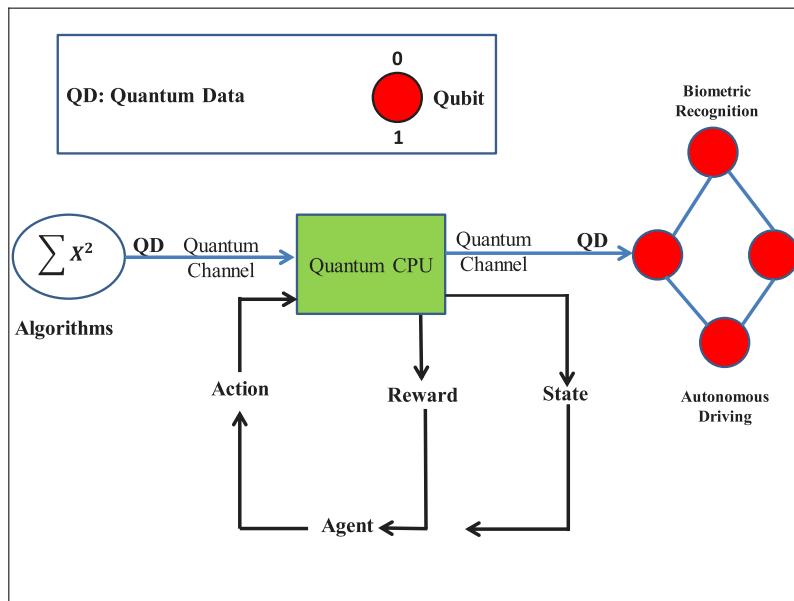


Fig. 5. Overview of Quantum Artificial Intelligence.

circuitry to preserve quantum superposition and entanglement. Quantum computers can handle and process exponentially larger amount of data than conventional computers can, because they intrinsically incorporate and manage the tensor product structure of composite quantum systems, which the number of parameters needed to obtain a complete description scale as 2^N , where N is the number of qubits. So, for instance, if $N = 100$ the vector space in which the quantum system evolves would have a dimension that is 2^{100} . That means that while we may need a 100 qubits on a quantum computer (assuming that we do not need error correction) to describe the evolution of composite system, the same described on a classical machine, would require 2^{100} parameters. It is then clear that quantum computers are intrinsically prepared in managing the evolution of systems described by a large number of parameters.

Quantum devices, coherently controlling quantum superposition and entanglement, can exploit *quantum parallelism*, i.e., they can simultaneously *explore* multiple evolution. For example, in classical decision the problem is often represented as a *decision tree*, where the evolution of the decision path is determined by a binary choice and the state of initialisation of the register. This method becomes less effective when the creation of branches from each decision split-point slows down because the time needed to obtain an outcome to decide the split is too long. Quantum devices, exploiting quantum superposition to initialise the input register, and quantum evolution (that coherently preserves superposition) may explore, simultaneously, the various possible branches of a decision, speeding up considerably the application of these kind of decision-tree approaches. It is still difficult to provide a certain foreseeable future for the development and to know precisely how and when we will have a complete and deep application of quantum advantage, however it is reasonable to say that the exponential speedup of quantum computing will involve all sort of problems with large amounts of data to manage, like pattern recognition, or training in machine learning models.

Training of machine learning models, like in reinforcement learning base much of their effectiveness on the speed at which the *agents* learn, interacting with the environment: They interact, obtain some feedback, and adapt (learning) their behaviour on the base of the feedback received. This approach has been confirmed, e.g., in a recent experiment [170] where not only the training of agents has been improved and accelerated by using a quantum channel, but it has been also integrated to implement a hybrid quantum/classical scenario, using a very promising integrated nano-photonics processor, where classical communication are used for tuning and to achieve the optimal control of the learning progress.

Clearly, if the computational speedup is exponential, as it is for quantum computing vs classical, when dealing with large amounts of data, such a speedup may have application on many different aspects of the development of AI. Fig. 5 provides a clear view of quantum computing with AI for modern applications.

Biometric recognition and autonomous driving are two critical examples that can utilise QAI for processing workloads. The fact that quantum computers can process more data in a shorter time than traditional computers has revealed the concept of QAI [171]. An example scheme for QAI is given in Fig. 5. QAI involves combination of Quantum Computing and AI to achieve superior performance results compared to classical AI [172]. Reinforcement Learning (RL) is a well-established branch of ML that aims to maximise the reward by trial and error by means of the agent [139]. It is certain that combining RL with Quantum Computing will lead to great advances in computing systems. With quantum computers accelerating machine learning, the potential for impact is certain to be enormous [173]. Applications of quantum AI for quantum search, quantum game theory, quantum Algorithms for decision problems, algorithms for learning are shown in Fig. 5.

The ability of quantum computing to execute a task quickly, may be helpful for AI systems employed, e.g., in problems related to autonomous driving natural, natural language processing (NLP) algorithms [174] and, in general, in tasks where classical approaches

are extremely time-consuming and expensive. Characters and words are the basis for the current algorithms. The idea of becoming “meaning aware” is a goal of quantum algorithms [175]. To build real-time speech patterns, these algorithms may use phrases and paragraphs. It is important to note that predictive analytics are a key AI application and commercial use case. Massive amounts of data can be used to train AI systems that are adept at machine learning and deep learning. However, complex and ambiguous issues such as stock market projections and climate change control systems require unique data created by quantum principles employing entanglement and superpositions [169]. New discoveries in Artificial Intelligence algorithms intended for quantum computers, or Quantum Artificial Intelligence (QAI), are expected to deliver the critical breakthroughs required to advance the science of climate change. Improvements in weather and climate forecasting as a consequence of this research are predicted to have a cascading effect on a wide range of socioeconomic advantages. For example, NASA has established the Quantum Artificial Intelligence Laboratory (QuAIL), which is dedicated to investigating the possibilities of using quantum computers and algorithms to machine learning problems in NASA’s missions.

Nanotechnology and nanoscience may also be integrated into AI for very small, microscopic devices at molecular, atomic, and subatomic levels, thanks to quantum computing. Quantum physics finds use in nanotechnology. These are only a few examples of quantum computing’s impact on AI and machine learning [176]. Machine learning applications for quantum devices are already being developed, in the hope to employ quantum computing to speed up the training of machine learning models and produce more efficient algorithms for learning [172]. Machine learning and artificial intelligence are likely to benefit from improvements in quantum computing technology even before a comprehensive quantum computing solution is ready. Hence, the field of Quantum Machine Learning (QML) is expected to pick up, followed by its autonomic expansion, Adaptive Quantum Machine Learning, which will be able to leverage quantum computing to adaptively achieve self-learning.

Open-source quantum machine learning library TensorFlow Quantum (TFQ) is available from Google [177]. Cirq is integrated with TensorFlow and provides high-level abstractions for the design and implementation of both discriminative and generative quantum–classical models by providing quantum computing primitives that are compatible with existing TensorFlow APIs, along with high-performance quantum circuit simulators. Quantum computing has, indeed, the potential to transform AI in a number of ways. Constraint resolution, uncertainty handling, and constraint fulfilment will all be improved by quantum computing, as will adaptive machine learning and spatial and temporal reasoning [178]. Even if quantum computing is still in its infancy now, from a commercial and economic standpoint, it is an excellent moment for startups to join this path. The future of our economy will not be decided by cryptocurrencies, but rather by quantum computing solutions [179].

4. Modern autonomic computing with embedded intelligence

This section discusses the new research developments related to autonomic computing with embedded intelligence. New advances in intelligent edge, intelligent things and sensors as actuators are detailed here.

4.1. Intelligent edge

IoT is bringing billions of new gadgets online, creating an unprecedented amount of data that will be challenging to manage. Over 75 billion IoT devices are expected to be in use by the year 2025, according to research [180]. Businesses are developing and installing more and more things meant to improve the end-user experience and also generate massive amounts of data, such as linked automobiles, smart metres, and in-store sensors. This new data, meanwhile, requires real-time collection, management, and processing [181]. Exactly how will this happen? One approach to go forward may be through the use of edge and fog computing [182].

Edge computing is expected to get a huge amount of attention than fog computing in the next years, but what exactly is it? As opposed to typical cloud computing, in which data is stored and handled in a central location, edge computing processes data on-the-fly [183]. The cloud and edge are not mutually exclusive in fog computing, which means that some computation can be done in the cloud, while other parts are handled by edge devices.

As a result, the data sent between linked devices might take too long, and edge computing utilises significantly less network capacity than traditional computing. Time can be saved by processing it locally on the device or inside a local network [66]. Edge computing, on the other hand, might provide cloud computing with much-needed assistance in dealing with the massive amounts of data generated by the IoT and other connected devices [169].

In both fog and edge, emerging IoT devices generate and transfer data, and the processing capacity of those devices is used to accomplish operations which might normally be carried out in the cloud. Both fog and edge allude to these new IoT device locations in the network. As a result, they help organisations lessen their dependence on the cloud by sending data to analytics platforms, where it can be analysed and turned into useful information. Corporations may cut down on network latency by using edge and fog technologies to reduce their reliance on cloud platforms for data analysis. As a result, you will be able to make data-driven decisions faster. In addition, because edge devices lack storage capacity, they must send data to the cloud when real-time processing is finished so that analytics may be conducted on it.

With today’s cloud computing, bandwidth, and processing power, business communication network focuses primarily on supporting all of your distant applications, as well as offering infinite storage space. That will eventually change. In order to get the most out of data, it must be processed in real time, at the edge [66]. Looking for future, network infrastructures must be more adaptive and willing to manage a far greater number of smart devices than they currently are now. Having the decision-making process near to where the data is created is essential for real-time intelligence. For example, self-driving cars or self-maintaining

smart manufacturing equipment can make fast judgements on the go [184]. Real-time engine performance data generated by sensors installed in aeroplanes can be used to take preventative action before the aircraft returns from the sky. The savings might be substantial. A company's ability to deliver processing power and an intelligent environment will increase as it expands its network of corporate endpoints.

We will need quicker and more reliable data processing as our demand for data grows and billions of devices are linked to the network. Despite the benefits of cloud computing, the development of IoT and mobile devices has necessitated ever higher bandwidth requirements [185]. Cloud computing is not required by every smart device, and avoiding transferring data back and forth over the cloud is a good idea in some circumstances. The edge may help enterprises become more nimble, decrease expenses, minimise latency, and better regulate network capacity [186].

How to provide enough computing power for intelligent applications at the edge has become a serious challenge. Intelligent edge is a promising way that pushes intelligence to the Edges of Internet, which has played the role of intelligent decision-making in many aspects of edge computing, including task offloading, edge caching, and resource scheduling. Among them, edge offloading is a distributed computing paradigm that provides computing services for edge caching, edge training, and edge inference. By integrating methods such as Distributed Machine Learning (DML), Deep Reinforcement Learning (DRL) and Collaborative Machine Learning (CML) into the edge computing, it is beneficial to cope with the explosive growth of communication and computing of emerging IoT applications [187], and achieve the energy-efficient and real-time processing [188].

Instead, single pass AI techniques that can operate on resource-restricted environments have been proposed. For instance, an alternative to traditional machine learning is data-stream mining. This ML paradigm treats its datasets as individual datapoints coming in one at a time, while performing adapting learning with a finite memory budget. From an autonomics perspective, data-stream mining also leverages the notion of adaptive concept drifts, i.e., to save resources on the edge, the data-stream model is retrained only when its performance crosses below a threshold [189].

4.2. Intelligent things

Intelligence integrated in a technology relates to the capacity of a product to analyse and consider its own performance. In addition, it must be able to deal with the workload and its own working conditions [190]. As a result of this, the overall experience of the end user is enhanced. When building a new products/services, it is important to keep in mind the notion of self-evaluation of the product based on data from embedded sensors [191]. A business intelligence system must be at the heart of an integral model to product or service introduction. Employing an embedded intelligent system and a machine learning algorithm model is a major benefit [192]. This may be assessed by looking at how well it performs in areas like launching smart product systems and setting up smart business services, to name just two. With the help of this cutting-edge infrastructure, it is possible to better understand and anticipate how the business landscape will shift in the future [193]. Because of this, it is an area where human analysts typically fall short. As a result, machine intelligence capabilities based on sensors integrated in current gadgets and goods have become a need in today's corporate environment [194].

The convergence of emerging applications and machine intelligence capabilities has led to an evolution in this process [190–194]. Embedded intelligence is increasingly being used to design the future IoT:

- AI: Human–machine intelligence synthesis is what this term denotes. In a specific gadget or service, the ability to make choices like the intellectual is possible.
- Data Integrity: Device history may be tracked using blockchain, a business intelligence application or innovation. Blockchain is made up of strings of interconnected block headers and blocks bodies [195]. The block body consists of all transactions in the block. The block header, on the other hand, is generated using the hash value, timestamp of the previous block, and a Merkle root of the transactions it contains. Therefore, each block is created using the hash value of the previous block and linked to each other. Interfering with any block will change the hash value of that block and thus all blocks will be affected. This promises the availability of Blockchain technology in protecting the integrity of data [196]. Blockchain technology, apart from cryptocurrency (e.g., Bitcoin), has been used to further enhance and optimise existing solutions such as cloud storage (e.g., [197]), authentication (e.g., [198]), health-care (e.g., [199]), and more. Integrating blockchain allows to have a clear audit trail of the data and models used to verify the machine decision process, which will lead to increasing the device's trustworthiness [200]. The latter is of extreme importance in machine-to-machine communication. Furthermore, running AI code over Decentralized Autonomous Organization (DAO) with smart contracts attached to it limits catastrophic risk scenarios by limiting the action space.
- Smart Healthcare: Utilising IoT in the healthcare business may pay out. As a result, healthcare would be even more widely available, and progress could proceed at a rapid pace.
- Predictive Maintenance: Predictive maintenance is a notion that has emerged as a result of the growth of the Internet of Things. This means the practise of adding sensors to household appliances so that they may send out notifications when they need to be serviced.

From natural language processing, face recognition, bio-medicine to autonomous driving, more and more intelligent applications are being deployed on IoT devices [201]. Due to the slow hardware development in small-sized equipment, the contradiction between the limited computing capacity of IoT devices and running complicated AI applications cannot be efficiently solved in a short time [202]. In addition, there remains significant challenges in developing system-level, algorithm-level, architectural-level or infrastructure-level technologies for embedded intelligence, e.g., real-time decision making, energy-efficient Deep Neural Network (DNN) training and DNN inference, and security deployments.

4.3. Things as sensor-actuator network

Cyber-Physical Systems (CPS) are the next generation of embedded Information and Communications Technology (ICT) systems that employ sensor-actuator networks to offer users with a wide range of smart applications and services by being aware of their physical surroundings [203]. With the help of autonomous control loops, many IoT sensors are conceivable because of the inclusion of improved processing and analysis of data collected by sensors, as well as planning and executing plans utilising actuators [204]. Methods are needed to aid in the design and development of these systems because of their complexity [205]. In the context of CPS, the systems that are embedded or software integrated into physical things, networked, and offering residents and companies with a wide range of smart applications and services are referred to as ICT systems [206].

Transport systems, buildings, electricity grids, and water infrastructure are all examples of CPS [207]. This type of CPS is meant to detect and react to the physical environment, allowing for quick, reliable autonomic control loops combining sensing and actuation, perhaps with linguistic and cognitive capabilities, as well [208]. Using wireless sensor/actor networks, CPS can monitor and respond to the physical environment. Sensors and other alternative sources collect historical and real-time data, which is used to perform advanced analysis and processing in the type of autonomic control loops [209]. These loops then plan and execute actions in accordance with a set of goals or rules. Real-time or historical data is used to support this implementation [210]. There are several elements that make CPS systems difficult to manage, including the use of a wide range of sensors and actuators, the necessity for real-time processing of enormous amounts of data, and the implementation of plans for issue solving [211]. As a result of the system's complexity, engineers need tools and techniques to aid them in the designing process; adaptive digital twins are poised to play a significant role in de-risking such complex engineering and cyber-physical projects.

5. Explainable AI (XAI) for next generation computing

Intelligent decisions are critical to the success of computing initiatives. Is a computing system stable and robust enough to execute workloads? Are the trained models black boxes or causally explainable? These are just a few examples of challenges that are faced before a computing system can be implemented [212]. Inaccurate decision-making is expensive in terms of both cost and resource usage when it comes to these complex and advanced technologies [213]. There have been a number of AI/ML applications in computing systems to enhance decision-making for allocation of resources and energy efficiency. Nevertheless, these AI/ML models' predictions for computing systems are still not practical, explainable, or executable [214]. AI/ML models are frequently hampered by these constraints. Even if QoS continues to be a primary concern, some recent research have turned their attention to explaining how QoS is achieved [215]. Is there anything that researchers can do to further the advancement of the computing community? As a result, a thorough understanding of Explainable AI (XAI) and hands-on expertise with XAI tools and approaches [216] is needed in order to make informed resource management decisions (an example application of AI for Computing). These issues may be addressed by using Explainable AI approaches, such as formulating predictions about resource and energy usage and SLA deviations and then implementing timely, intelligent action to solve them. In order to make computing more feasible, explainable, and executable, XAI prediction models must be properly implemented.

6. Potential risks of AI-integrated computing

AI can save money, but it requires a highly-trained workforce, that can be expensive at the start. AI's other drawbacks in computing systems would also include the following ones:

- Internet Connectivity Issues: ML/AI techniques based on autonomous computing are frequently hindered by slow internet connections. There seems to be a latency between transferring information to the cloud/fog/edge and receiving replies. ML methods for servers are prone to this issue since forecasting speed is among the most important considerations.
- Privacy of Data: AI systems need an enormous quantity of data, which include information on customers and providers. Understanding who owns the data is far more beneficial than having private information that cannot be attributed to a specific individual. Challenges about data security and compliance with regulations arise frequently when businesses utilise confidential material. Autonomic computing with AI necessitates consideration of privacy regulations and data security.
- Possibility of Errors: Although AI may seem exciting, like with any innovative technology, it is not always effective in accomplishing its goals. During its search for solutions, an AI system may generate many problematic statements on sensitive topics. With AI, there is a high risk of grave mistakes because of the many options and their implications. Before further usage of this innovation, trust and control must be established.
- Over-reliance on AI Models: As it stands, AI/ML algorithms are only a small part of complex software-intensive systems. Software engineers leverage them for completing highly specialized tasks, while designing a large apparatus of more traditional algorithms around them, including sensor-data sanitization and filtering. Further, an AI model is only as good as the data it was trained on. Hence, strong data engineering processes are required to select appropriate/representative datasets and conduct various data engineering steps as well as thorough review processes need to be followed when transfer learning models are selected. From an autonomic perspective, all these steps need to be carefully handled by the MAPE-K loop, which will essentially need to act both as a software and a data engineer when conducting adaptations to the ML models.

Hype Cycle for AI-integrated Next Generation Computing

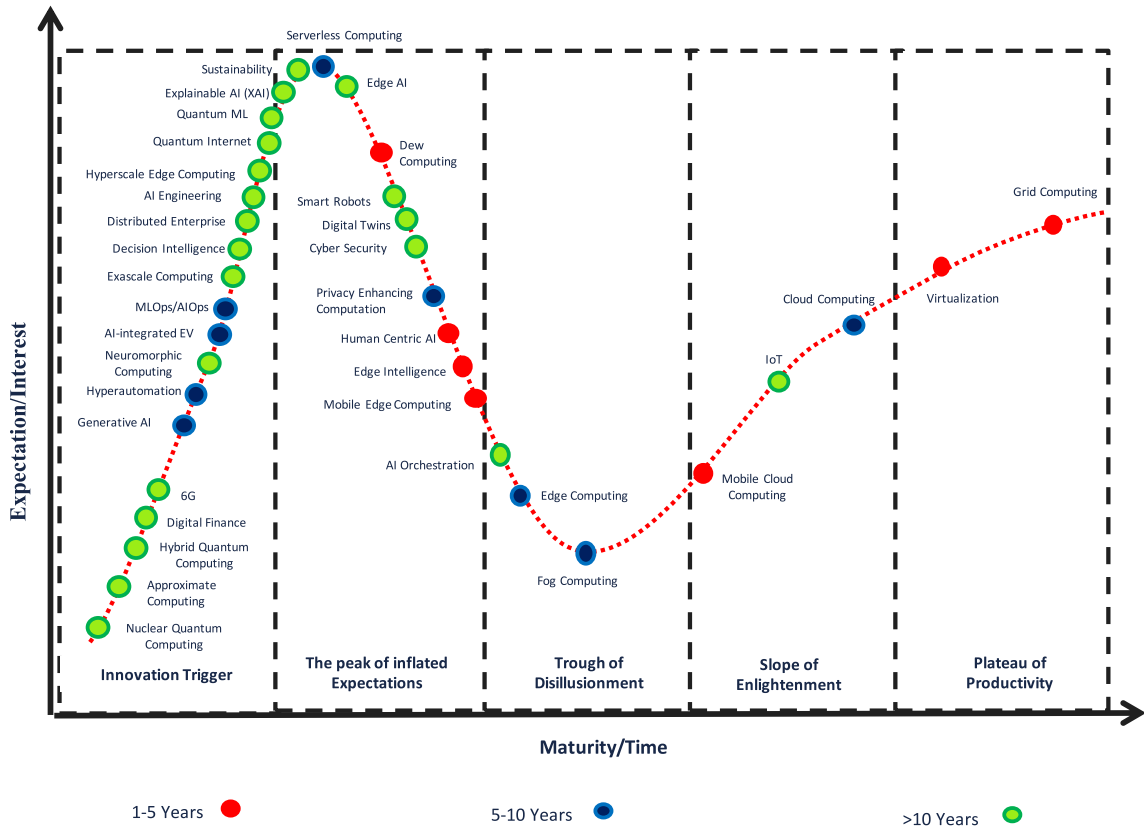


Fig. 6. Hype cycle for AI-integrated next generation computing.

7. Emerging trends and future directions

On the basis of current research, we have selected a number of computing study fields for three distinct maturity levels (5 years, 5 to 10 years, and more than ten years). We have identified a number of emerging technologies over the next decade, all of which have the potential to make efficient use of AI/ML-integrated next-generation computing [122,217–219]. Fig. 6 depicts the hype cycle for next-generation computing. There has been a lot of study done on cloud computing and IoT, but serverless computing is currently at its peak. Under the umbrella of computing, research fields including fog computing, edge computing, AI Orchestration, and mobile edge computing are only getting started. It might take up to ten years for the application of computing in these fields to reach maturity. However, the hype cycle for Explainable AI (XAI), AI engineering, hyperscale edge computing, distributed enterprise, sustainability, quantum Internet and quantum ML is projected to last more than ten years. The hype around smart robots, digital twins, cyber security, edge AI, human-centric AI, edge intelligence, dew computing and privacy enhancing computation is at an all-time high. It is anticipated that they will be fully developed in less than five years under the umbrella of autonomous computing. Expected to significantly evolve in the next five to ten years, MLOps, AIOps, AI-integrated electric vehicles (EV), decision intelligence and exascale computing have likewise hit their height of overblown expectations. Generative AI, hyperautomation, neuromorphic computing, hybrid quantum computing, digital finance, 6G and quantum computing all have a long way to go before they reach the heights of the hype cycle. Grid computing and virtualization have received a lot of attention in the past several years, and they might continue to do so over the next five years.

In the following, we have highlighted a number of unsolved problems and research paths that require further investigation.

7.1. Cloud computing

- New ensemble machine learning approaches for container management systems, such as Docker Swarm and Kubernetes, are needed to govern user-based QoS-based container clusters.
- Cloud service dependability and QoS must be maintained through the use of advanced machine or deep learning techniques.

- Network virtualization must be provided at a reasonable cost in an SDN-based cloud computing environment that uses AI/ML models to minimise energy consumption and boost dependability.
- Using AI/ML, cloud-based Big Data analysis tools may find trends in client behaviour, make better decisions, and better understand their customers. It is a difficult challenge that has to be solved in order to ensure that scaling choices are executed or processed in a timely manner utilising AI/ML.
- Thermal-aware task and resource scheduling can be improved by using new AI/ML-inspired methodologies.
- AI/ML-based autonomic computing is becoming increasingly important as the IoT and scientific applications grow.

7.2. Fog computing

- It is imperative that the newest AI and ML approaches be used in order to forecast security vulnerabilities in the fog layer and IoT devices because of their intrinsic decentralisation.
- AI-based deep learning approaches are needed to estimate resource requirements in advance for different geographic resources for fog and cloud computing, which need new policies for provisioning and scheduling resources.
- On diverse fog environments, state-of-the-art AI/ML approaches may be employed to schedule tasks.

7.3. Edge computing

- Modern computing systems, which incorporate edge devices as component of datacenters, demand specific IoT-based apps to be created in order to provide for more encrypted transmission and to protect the privacy of data.
- Due to the resource limitations of IoT edge devices, which cannot run the robust security software and firewalls built for desktop PCs, Blockchain technology must be used to enhance security using AI/ML. Moreover, innovative software architectures such as that facilitate IoT devices patching and maintenance could be further enhanced by leveraging AI and ML.
- AI/ML-based automated decision-making, rather than human-encoded heuristics, presents a lucrative path for optimising edge systems with massive volumes of data through engineering speed and efficiency.
- AI-based big data analytics methods are needed to handle edge device data in IoT applications at runtime.

7.4. Serverless computing

- AI may be used to enhance the delay and reaction time of tasks in Serverless computing for IoT applications.
- Automatic heart disease detection in IoT and Serverless computing contexts requires an ensemble deep learning-based intelligent healthcare system.
- How can deep learning on IoT devices increase real-world performance in AI-based intelligent systems by leveraging Serverless Computing?
- Serverless systems can benefit from threat mitigation strategies based on AI/ML, such as clustering model-based security analysis.

7.5. Quantum computing

- To *increase the size* of current quantum chips, keeping under control the amount of noise present during the evolution of the quantum states.
- To enter, in full, within the era of Noisy Intermediate-Scale Quantum (NISQ) devices, which should allow us to simulate the dynamics of *complex* quantum systems.
- To integrate quantum chip with quantum error correction (QEC) that will allow to progress towards Fault-Tolerant Quantum Computation (FTQC). That will allow to simulate the design and behaviour of novel materials on general purpose quantum computers, opening up new possibilities in virtually all area of knowledge, from physics matter to the design of novel AI applications.
- Develop cloud quantum computing infrastructures that, very likely, will be the way in which we will use quantum computer and simulators: as a booster supporting our local, classical devices.
- To handle the massive amounts of data created by IoT devices, powerful AI and reinforcement learning may be used.
- The most recent AI and ML-based methods may be utilised to dynamically discover and rectify faults to provide a valued and dependable service. Recent AI and ML approaches can enhance dependability, but they can also raise system complexity by increasing data processing, which results in higher training costs for AI and ML techniques as a side effect.

7.6. Miscellaneous

The advancements in cloud, fog, and edge in the context of IoT have led to concepts such as Cloud-to-Things. The following are interesting research directions to explore:

- The ability to form Decentralized Autonomous Organizations (DAOs) is a concept fundamental to the Cloud-to-Things computing continuum.
- Rules and agreements can take the form of Blockchain-enabled smart contracts, thus providing for trust among the actors and organising computing across the continuum [220].

AI/ML can also open up new research directions when used in conjunction with blockchain technology:

- Smart Oracles can be used to establish decentralised monitoring of vertically and horizontally distributed heterogeneous infrastructures.
- AI/ML and knowledge management methods can be incorporated both within functions of Blockchain-enabled smart contracts and Smart Oracles.

8. Conclusions and summary

Computing systems have advanced computer science in the past couple of decades and are now the heart of the corporate world, providing services based on Cloud, Fog, Edge, Serverless, and Quantum Computing. Many real-world problems that require low latency and response time have been solved due to modern computing systems. This has helped young talents around the globe to launch start-ups allowing large computing capacity for solving challenging problems to speed up scientific progress.

Artificial Intelligence (AI), Machine Learning (ML) and Deep Learning (DL) have become increasingly popular in recent years because of the advances in accuracy pioneered by them in areas such as computer vision, natural language processing and other allied applications. For training these models, massive amounts of data has been collected in the previous few years in addition to the development in state-of-the-art computing hardware such as the Graphics Processing Unit (GPU), Google's Tensor Processing Unit (TPU) and AI Tesla's Dojo Processing Unit (DPU). Computational researchers and practitioners should be aware of AI/ML/DL algorithms and models. With AI/ML/DL, modern computing may profit from more efficient resource management, while computing is a vital platform for hosting AI/ML/DL services because of its huge computational capacity. This means that both sides gain from the other. Large-scale computing power and external data sources are needed for many AI/ML/DL techniques, which may be more easily obtained via computing systems. This is especially important now that methods for training sophisticated AI, ML, and DL models can be implemented in parallel and in large quantities. To that end, it is foreseen that continued interest in AI/ML/DL applications will spur new research into well-established data centre resource management issues including VM provisioning, consolidation, and load balancing, while also making it easier to cope with scale-out challenges. Innovative research on Explainable AI (XAI) might pave the way for more widespread use of AI in modern computer systems.

AI and ML are bringing important necessary demands for computing systems in the upcoming years, from large-scale heterogeneous IoT and sensor networks generating extremely huge data streams to store, maintain, and investigate to QoS-aware (latency, energy, cost, response time) customised computing service adapting for an array of hardware devices while maximising for multicriteria including software-level QoS constraints and financial restraints. As a result of these needs, new methodologies and research strategies are needed to harness the AI and ML models in order to overcome the challenges such as latency and scalability as well as resource and security management. As a cost-effective technique to increase computing application performance, scaling and flexibility are functional abilities that are yet to completely utilise AI and ML models. AI and ML may be strategically used in resource management and scheduling techniques to maximise QoS to improve modern computing. At this time, there are no comprehensive models of service resilience, autonomous methods for managing availability and reliability, and provisioning algorithms that are cognisant of failures in the current research. Next-generation or futuristic computing could be established with the help of AI/ML techniques, which can handle these problems quickly and effectively. The implementation of AI/ML-based resource management policies can help data to automatically adjust their own energy usage and deliver QoS without affecting the system's reliability. AI and ML techniques may also be used to predict the demand for energy usage in advance by combining renewable and non-renewable energy sources. Further, AI/ML modes can be used to analyse Big Data for security breaching. Fig. 7 shows the summary of new trends and future directions for AI-integrated next generation computing.

In this article, we have given our vision and explored numerous new trends in AI and ML for cloud, fog, edge, serverless and quantum computing, as well as for other computing platforms and technologies. This is a holistic futuristic research article that has drawn together breakthroughs and highlighted the obstacles remaining to be solved in implementing the use of AI/ML for modern computing. We have also developed a conceptual framework for integrating cutting-edge technology in the future to provide effective computing services. New research developments related to autonomic computing with embedded intelligence have been discussed. In addition, various potential risks of AI-integrated next generation computing have been presented. This work recognised recent significant challenges in AI/ML-embedded next generation computing and has summarised research findings with limitations. Additionally, this futuristic work has examined how current computing issues would be affected by new trends. In this visionary work, potential research directions for AI/ML-based next-generation or modern computing are highlighted. It is clear that AI and ML can be used to solve complicated issues in the future, and this forward-thinking strategy inspires other scholars and researchers to follow suit in a similar fashion. We expect that this visionary research will be useful to practitioners, scientists, engineers and researchers who are interested in conducting research in any area of AI/ML-integrated next generation computing in the future.

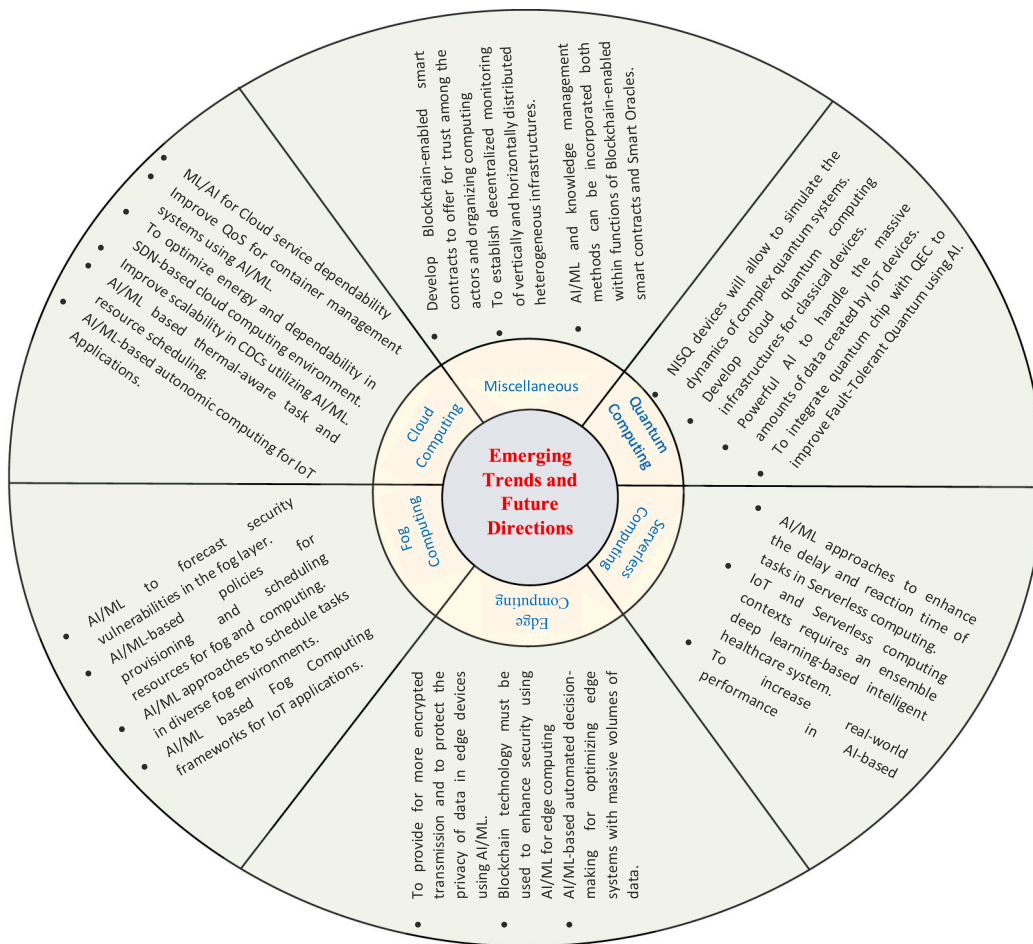


Fig. 7. Summary of emerging trends and future directions for AI-integrated next generation computing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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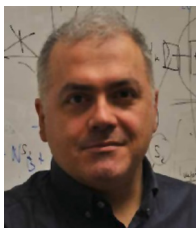
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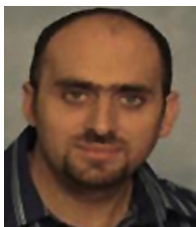
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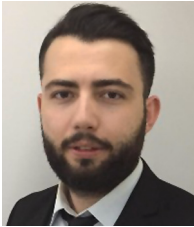
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Artificial Intelligence and Human Resources Management: A Bibliometric Analysis

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ABSTRACT

Artificial Intelligence (AI) is increasingly present in organizations. In the specific case of Human Resource Management (HRM), AI has become increasingly relevant in recent years. This article aims to perform a bibliometric analysis of the scientific literature that addresses in a connected way the application and impact of AI in the field of HRM. The scientific databases consulted were Web of Science and Scopus, yielding an initial number of 156 articles, of which 73 were selected for subsequent analysis. The information was processed using the Bibliometrix tool, which provided information on annual production, analysis of journals, authors, documents, keywords, etc. The results obtained show that AI applied to HRM is a developing field of study with constant growth and a positive future vision, although it should also be noted that it has a very specific character as a result of the fact that most of the research is focused on the application of AI in recruitment and selection actions, leaving aside other sub-areas with a great potential for application.

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Artificial Intelligence: A New Paradigm in Human Resource Management

The supposed “Fourth Industrial Revolution” or “Industry 4.0” has introduced intelligent technologies like Artificial Intelligence (AI) (Kong et al. 2021). The increased development of information and communication technologies (ICT) allows phenomena like AI to greatly influence different parts of society (Bolander 2019) becoming one of the most relevant elements of all possible changes in various aspects of life in this era (Aloqaily and Rawash 2022)

Although different departments of multiple organizations have adopted or integrated AI-based tools, the Human Resources (HR) department still cannot implement them (Vrontis et al. 2022). Despite there being many people in the HR department of organizations that recognize the importance of applying AI, they also point out that they have not taken any actions regarding this. This is a reality that shows that even though AI in the HR area is still a developing

revolution and is mostly limited to large companies (Bolton 2018), it is already unstoppable.

Due to the relative novelty of this technology and its application in different areas of the organization, many of the scientific developments in this field have mostly occurred in recent years. For this reason, although AI has been presented as a powerful tool in HRM, academic research on the subject is not very extensive (Pan et al. 2022).

In this context, we consider that based on a bibliometric approach, the article aims to identify and analyze the connection of the AI phenomenon with the human resource management (HRM) of organizations to study (1) the level of knowledge and training of their managers, (2) the benefits and challenges in its implementation, and (3) identify the subareas with greater development and implementation in HRM.

The connection between AI and HRM allows us to establish the following research questions for this work. The first research question is related to previous AI reflections and challenges. However, authors seem unclear how AI will affect or benefit employees and societies (Mitchell and Brynjolfsson 2017). Other authors point out to the need for more data about on the speed of AI progress (Nedelkoska and Quintini 2018). Especially its impact on every HRM-related task.

RQ1. Does the scientific community consider AI to be a commonly used tool in HRM?

The second proposed question has been studied by several published works that indicate the benefits of AI technology in different HRM sub-tasks (Qamar et al. 2021).

RQ2. Does AI have a similar impact on all HRM sub-areas?

RQ3. Are employees in HR areas prepared to meet the challenges posed by AI in people management?

RQ4. Does the application of AI in HRM help to improve the company's competitiveness?

The answer to this research questions derived from the results obtained together with the discussion and the most relevant conclusions support the theorization presented in this paper. Regarding the originality of this work, this study, based on quantitative and qualitative research, from the combined use of the most relevant scientific databases, Web of Science and Scopus, allows us to focus on how IA has been integrated into organizations in HRM and its influence on the

Table 1. Definitions of Artificial Intelligence.

Authors	Definitions
(McCarthy 1956)	The science and engineering of creating intelligent machines, especially intelligent computer programs.
(Minsky 1968)	The science that deals with the development of machines capable of performing functions that a human can perform and that require human intelligence.
(Nilsson 1998)	AI is a part of computer science that focuses on machine learning, making computers act intelligently, continuously learning, and improving their performance.
(Cappelli et al. 2019)	Broad class of technologies that enable a computer to perform tasks that normally require human cognition, including decision-making.
(Stanley and Aggarwal 2019)	Development of computer systems that perform tasks that require human intelligence. The main goal of AI is to make machines more intelligent.
(Bolander 2019)	Construction of machines – computers or robots – that can perform tasks that otherwise only humans have been able to do.
(Paesano 2021)	Systems that exhibit intelligent behavior by analyzing their environment and performing actions, with a certain degree of autonomy, to achieve specific objectives.

approach of organizations and Human Resources. The results obtained will allow make the following contributions. First it will serve the research community in the AI field and its applications in the management of people and talent in organizations as a starting point for future related research work. Also important will be the implications for the people responsible by allowing the knowledge of the main uses and applications of new resources and tools in the HRM of organizations will also be relevant and current trends in their application.

Concept of Artificial Intelligence

The concept of AI has multiple definitions. Different researchers have proposed their definitions (Welsh 2019). Depending on the time and the level of technological development reached, different studies have focused on its various aspects. A sample of the most relevant definitions since the 20th century is shown in Table 1.

Despite the ambiguous origin of the concept of AI, two authors stand out in its development. On the one hand, we have A.M. Turing, the father of modern computation, while on the other hand, there is J. McCarthy, the father of AI. Turing (1937) introduced the concept of algorithms and laid the foundation of computer science. Later, Turing (1950) proposed the Turing test, which tests whether a machine has the capacity to be as intelligent as the person performing its functions. However, J. McCarthy coined the term “artificial intelligence” during a conference in Dartmouth (Paesano 2021). In the 1950s and 1960s, AI was expected to develop rapidly into computers and robots with human-level cognitive capabilities, but that did not happen until it recently gained prominence (Bolander 2019; Pillai and Sivathanu 2020).

Artificial Intelligence Applied to People Management

Human capital is a differentiating element of an organization as it is an intangible resource that is difficult for competitors to imitate, thus giving a potential competitive advantage to any organization (Kearney and Meynhardt 2016).

HRM has become a strategic trend in organizations due to economic, political, social, and especially technological changes (Jatobá et al. 2019). Not all departments have embraced this new role, and strategic positioning remains slow and sometimes problematic (Poba-

Nzaou et al. 2020). In these cases, incorporating technologies like AI requires the need to evolve with the other facets of society (Michailidis 2018).

The role of AI in an organization is to improve efficiency and effectiveness of the HR function by making the various management processes agile and accurate (Nankervis et al. 2021). For HRM, IA will enable the understanding and control of a data collection process so that this process is included in an organizational and economic efficiency strategy (Varma et al. 2022). Among the different areas that make up the HRM in an organization where AI is starting are: (1) talent search and recruitment, (2) training and development, (3) performance analysis, (4) career development, (5) compensation, and (6) staff turnover (Abdeldayem and Aldulaimi 2020; Nawaz 2020; Qamar et al. 2021; Yahia, et al. 2021)

Qamar et al. (2021) showed that AI has been implemented in HRM in various organizations via the following techniques:

Expert Systems: They are programs designed to configure expert knowledge into logical structures that solve unstructured problems and help develop complete information systems by providing easy access to knowledge. It is applied mainly in HR planning, compensation, recruitment, and labor management (Malik et al. 2022).

Fuzzy Logic: This technique is used in different research fields (Salmerón and Palos-Sánchez 2019). In the case of HRM, it's based on set membership levels, whose values vary between 0 and 1. A value of 0 indicates no membership, while a value of 1 shows full membership. With these sets, fuzzy logic can quantify data uncertainty and foresee future scenarios to facilitate decision-making (Kimseng et al. 2020). Its application began in 2000 and was used in personnel selection and optimal workforce design (Qamar et al. 2021).

Artificial Neural Networks: This application is a simplified model developed to mimic the function of a human brain. Its structure comprises a processing element, a layer, and a network to recreate the human learning process (Huang et al. 2006). It is one of the most popular techniques for prediction and is mainly used in selection, recruitment, and personnel performance management (Qamar et al. 2021).

Data Mining: It is the extraction of valuable but hidden information. Through its application, organizations can transform useful information and patterns into competitive advantages (Huang et al. 2006). Data mining was used in HRM in 2006 and has been applied mainly for recruitment, competency and performance evaluation, and talent management.

Genetic algorithm: These information search techniques based on replication, mutation, and gene crossover arrive at optimal solutions to mathematical problems. It is used mainly in workforce planning and personnel performance evaluation (Zhang et al. 2021).

Machine learning: It is the learning process by which a machine can learn by itself without being particularly programmed to do so (Rąb-Kettler and Lehnervp 2019). Several papers agree that the use of machine learning in decision-making is quite beneficial for HR managers and turnover prediction (Hamilton and Davison 2022).

Benefits and Challenges of Artificial Intelligence in Human Resources Management

As with any technological advance, AI brings both benefits and challenges, and its application in HRM is no different (Vrontis et al. 2022). These can be approached from three points of view: employees, company, and society.

We highlight the following potential benefits:

Employees: The automation of repetitive and time-consuming tasks allows HR managers to focus on those tasks that add value and require unique skills and abilities (Pillai and Sivathanu 2020). The reduction or minimization of errors owing to machine learning also helps improve decision-making by providing more and better-processed information (Michailidis 2018). According to a 2019 survey, 61% of companies were using AI to improve HRM in key AI-transformed HRM areas. This task will include time-consuming and labor-intensive processes in recruitment, such as reading many CVs, sorting through them and identifying the best candidates and detect employees who need some training (Rykun 2019)

Company: For companies, AI means greater effectiveness and efficiency as it streamlines management processes and reduces associated costs (Nankervis et al. 2021). It enables greater candidate outreach as it reaches passive candidates who are not in active job search but might become interested in the position (Black and van Esch 2021). Another important element for companies is the improvement of communication and interaction possibilities among employees (Michailidis 2018). Research articles look at how AI help to improve the successive stages of the recruitment process: identifying, selecting and retaining talented people (Allal-Chérif et al. 2021).

Society: The creation of new professional profiles linked to AI, like robotics specialists, data scientists, deep learning experts, generate new scenarios which can benefit the public (Michailidis 2018).

As far as challenges are concerned, the following can be highlighted:

Employees: The application of AI may contribute to burnout, with some employees being worried about their career uncertainty, since machines may replace them, thereby creating anxiety and job insecurity (Kong et al. 2021). There is also dehumanization of personal relationships, as some of the HRM processes may be performed entirely by machines, like the use of chatbots (Fritts and Cabrera 2021). This implies the continuous need for training in technological matters. Finally, it is necessary to point out that the “techno-stress” is a consequence of excessive and continuous use of any type of technology (Malik et al. 2021).

Company: The need for highly qualified personnel to manage and acquire the necessary skills to keep up with the increasing technological developments (Abdeldayem and Aldulaimi 2020) is a reality in AI. Even though it has high implementation costs, it can reduce costs in the processes where they are applied (Michailidis 2018). Another challenge is the existence of biases due to the use of small and non-representative data volumes (Soleimani et al. 2022) and the increased exposure of the company leading to increased risk of its data security breach (Malik et al. 2021).

Society: One of the main challenges in this area is the “technology gap” Since technology in general and AI has divided the world, it has created greater technological inequality. This is because not all countries can implement and maintain technological infrastructure (Abdeldayem and Aldulaimi 2020). Potential job losses in certain professions are also important in the face of these challenges (Hamilton and Davison 2022).

Methodology

The methodology used was bibliometric analysis using the Bibliometrix application. This tool was developed by Aria and Cuccurullo (2017) to carry out comprehensive analyses of the scientific mapping of a topic. It is an open-source tool to perform a comprehensive analysis of the scientific literature. It was programmed in R language to be flexible and facilitate integration with other statistical and graphical packages. Bibliometrix enables the structured analysis of large amounts of information to infer: (a) trends over time, (b) which topics are being investigated, (c) changes in the boundaries of disciplines, etc., thus summarizing a topic (Guleria and Kaur 2021).

The first step was to determine the databases to be used for the document search. The databases being queried were Web of Science and Scopus, as they are currently the most relevant within our research field (Parris and Peachey 2013). The search keywords on both bases were “*Artificial Intelligence*” and “*Human Resources*” in the search field (Article Title, Abstract, and Keywords) (Macke and Genari 2019) for the period 2018–2022. This period was chosen based in previous authors. For Kshetri (2021) AI-based HRM applications can bring about significant changes in human resource management practices. However, previous researchers have observed a substantial gap between the promise and reality of AI in HRM (Michailidis 2018; Tambe et al. 2019). The research domain of AI in HRM is relatively nascent (Strohmeier and Piazza 2013). Garg et al. (2022) note the narrowing of the gap between the number of journal and conference papers from 2017 onwards: a decrease in conference papers with a simultaneous increase in journal papers shows the increasing confidence, interest, and acceptance for AI, especially Machine Learning (ML).

Based on all this, the choice was justified because (1) it had the highest number of publications on the issue, (2) it had an interest in the topic, and (3) the previous literature does not correspond to the current technological level.

Subsequently, the scientific fields selected for the query were (1) Business, (2) Management and Accounting, (3) Arts and Humanities, (4) Social Sciences, (5) Economics and Finance, and (6) Psychology and Research Management. These areas were chosen since they were directly related to our current scenario. The scientific fields that could contribute the least to research, such as physics, biology, medicine, etc., were eliminated. The analyzed works were those written in English to cover a larger number of publications (Gutiérrez and Maz 2004) and limited to those publications that were only articles (Podsakoff et al. 2005) excluding works corresponding to the following types of documents: (a) book, (b) book chapter, (c) proceedings paper, (d) review and (e) editorial material (Vlačić et al. 2021).

Once the search string was established and the corresponding filters applied, we obtained 156 articles. As shown in Figure 1, among the 89 articles initially obtained (63 in the Scopus database and 26 in Web of Science), 9 were rejected after further analysis of their content. This resulted in 80 valid articles for the study. Finally, 7 of these were eliminated as duplicates were found. Thus, we finally obtained 73 papers due to the harmonization of the results.

The final articles were exported from the databases in their respective formats; Plain text and BibTeX for Web of Science and Scopus, respectively. They were then integrated into a single format to be imported later into the Biblioshiny platform and further data analysis was carried out. Before processing the data with this software, the following steps were adopted: (1) Download and install the latest version of R and RStudio (<https://cran.r-project.org/> and <https://www.rstudio.com>) (2) Open RStudio and in the console window type the following command to finish the installation of Bibliometrix;

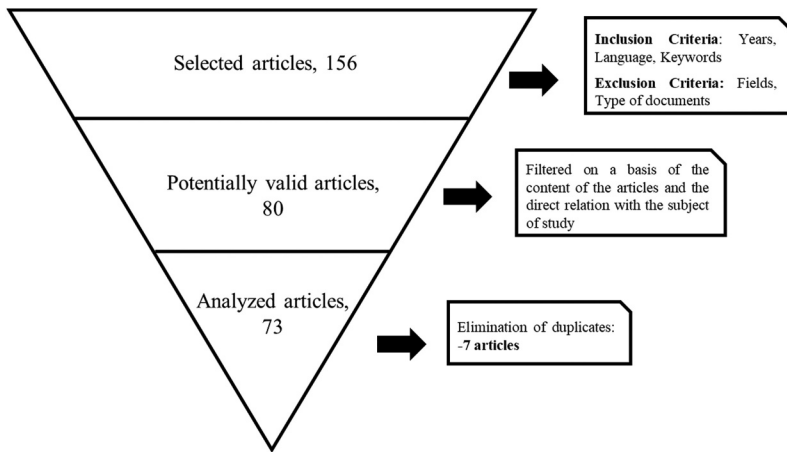


Figure 1. Identification of articles to be analyzed.

install.packages("bibliometrix") (3) Type the following command to be able to run the Biblioshiny program: *library(bibliometrix) biblioshiny()*

According to Iden and Eikebrokk (2013) and to the established inclusion and exclusion criteria the data extracted from each study were as follows: (1) the journal and full reference, (2) the authors and their institutions, (3) the countries where they were situated, (4) the keywords, (5) classification of the research methods, (6) theoretical frameworks and references theories used, (7) main topic area, (8) research questions and (9) a summary of the study.

The critical examination of the content of each article (Bellucci et al. 2021) together with the use of the Bibliometrix tool, in particular, by means of Multiple Correspondence Analysis (MCA), made it possible to establish three thematic clusters: (1) AI in HRM, (2) Digital Recruitment and (3) Electronic HR. According to Paul et al. (2021) the systematic review of a topic in depth and with rigor favors both the theory on an area and the research methodology in that field can benefit, this is our purpose with the development of this work in the field of IA and HRM.

Results

AI is undoubtedly one of the most important innovations. Both academics and practitioners hope that IA can solve this problem and offer a solution to support and streamline innovation processes. However, the literature on this topic is fragmented (Pietronudo et al. 2022). These authors concluded that AI renews the organization of innovation and AI triggers new challenges. That is, they suggest that AI is not a tool that uniformly optimizes innovation management and decision-making but is better understood as a multifaceted solution.

Similar conclusions can be reached by first analyzing other systematic literature reviews (SLRs) and a bibliometric analysis. Table 2 shows SLR

works approach these reviews from different points of view applied to a greater or lesser extent to different HRM processes.

The 73 articles were published in 53 different journals and represented 199 different authors (Table 3). The average number of annual publications represents an average of < 1 article per year, thereby indicating, at first glance, that the field of AI being applied to HRM is underdeveloped. However, as shown in Figure 2, it is a topic of great interest in the immediate future.

The annual distribution of the number of articles shows the general state of research and trends, with exponential growth occurring only in the last five years. Advances and growth in the importance of AI in both academia and HR (Jatobá et al. 2019) have sparked increased interest in investigating the influence of one topic on the other. Although there were only two articles in 2017 addressing the concepts in a connected way, the number increased to 10 in 2019. The trend line shows that AI will soon persist in the future as one of the top world innovations (Qamar et al. 2021) with an annual growth rate: 64.38%.

Analysis of Sources

Table 4 shows, in order from the highest to the lowest number of articles, the main journals that published on these analyzed realities. The journal with the highest number was “International Journal of Manpower” with six articles, followed by the “International Journal of Human Resource Management” and the “Business Horizons” with five and four articles, respectively. The journals with the highest number of publications on these topics were journals related to business or technology, with a focus on HR, like “Advances in Developing Human Resources and/or Human Resources Management,” is also gradually gaining importance.

Another fundamental indicator called “Bradford’s Law” was used to analyze the main journals and their importance in the field (Bradford 1976). This law allows researchers to access those journals that provide the most information on a topic, thus reducing their search times (Figure 3).

Another fundamental indicator called “Source Growth” was used to analyze the main journals and their importance in the field. This figure allows researchers to know the evolution of those journals (see Figure 4). The journals “Ethics and Information Technology” and “International Journal of Human Resource Management” present an important growth trend.

The most cited journals were “Business Horizons,” “International Journal of Human Resource Management” and “International Journal of Manpower,” with 138, 87, and 12 citations, respectively (see Table 5).

The g-index is calculated from the distribution of citations of an author’s publications, which results in a set of articles ranked in decreasing order by the number of citations they have. The Hirsch index (h-index) uses the set of the author’s most cited articles and the number of citations it has received in other

Table 2. Previous AI and HRM Literature Overviews.

Authors	Type/Period	Data sources ^a	Context	Screened works/ primary studies	Methodology based
(Vrontis et al. 2022)	SLR unspecified	3,4	Holistic SLR on HRM strategies, namely: job replacement, human-robot/AI collaboration, decision-making, learning opportunities, and HRM activities: recruiting, training and job performance	45/187	(Tranfield, Denyer, and Smart 2003); (Crossan and Apaydin 2010)
(Votto et al. 2021)	SLR 2014–2020	1,3,5,6	Explore Tactical HRIS literature and come to understand which components are exist in literature and how they are further represented.	33/697	Tactical HRIS (T-HRIS) components
(Garg et al. 2022)	SLR 2002–2018	2	Semi-systematic literature review; understand current state of Machine Learning (ML) integration within HRM; showcase relationship between HR experts and ML specialists	105/168	(Wong et al. 2013) (Snyder 2019)
(Qamar et al. 2021)	SLR –July 2020	2	SLR of AI and HRM to capture current state-of-the-art and prepare for new research agenda	59/308	(Tranfield, Denyer, and Smart 2003) (Pickering and Byrne 2014)
(Di Vaio et al. 2020)	SLR/Bibliom 1990–2019	1,15	Comprehensive review of relationship between AI and sustainable business models, in special Sustainable Development Goals (SDGs). The SLR paper aims to highlight the role of Knowledge Management Systems (KMS).	73/88	Identify research gaps between knowledge management systems and AI

(Continued)

Table 2. (Continued).

Authors	Type/Period	Data sources ^a	Context	Screened works/ primary studies	Methodology based
(Basu et al. 2022)	SLR un-specified	1,5,6	AI – HRM Interactions and Outcomes: A SLR and Causal Configurational Explanation. Content analysis and thematic abstraction.	100/433	(Denyer and Tranfield 2009)
(Coron 2022)	SLR 2000–April 2020	7	based on an integrative synthesis of empirical and non-empirical articles on the use of quantification in HRM. Integrative and systematic synthesis procedure	94/103	(Briner and Denyer 2012)
(Bilan et al. 2022)	Bibliom.1983–2020	2	Bibliometric Review of AI Technology in Organizational Management, Development, Change and Culture	191/218	unspecified
(Bhatt and Muduli 2022)	SLR 1996–July 2021	8,9,10,11,12,13,14	AI in learning and development	81/115	(Tranfield, Denyer, and Smart 2003); (Crossan and Apaydin 2010)
(Pereira et al. 2021)	SLR 1995–2020	1,3	Impact of AI on workplace outcomes: A multi-process perspective. Limit to peer-reviewed journals ranked 3, 4 or 4* in the AJG (formerly ABS) 2018 journals.	56/211	(Tranfield, Denyer, and Smart 2003)
(Perello and Tuffaha 2021)	SLR 2010–may 2020	2,13	AI definition, applications and adoption in Human Resource Management	66/559	(MacKenzie et al. 2012); (Denyer and Tranfield 2009)

^a1: ISI Web of Science; 2:Scopus; 3: Business Source Ultimate (EBSCO); 4: Science Direct; 5: AIS; 6: ABI; 7: Journal Quality List (JQL) database; 8: Emerald; 9:Taylor & Francis; 9: Springer; 10: Sage Publications; 11: Massachusetts Institute of Technology Sloan Management; 12: Harvard business; 13: Science

Table 3. Summary of bibliographic information.

Description	Results
MAIN INFORMATION ABOUT DATA	
Period Time	2017:2022
Sources (Journals, Books, etc)	53
Documents	73
Annual Growth Rate %	64.38
Document Average Age	1.33
Average citations per doc	6.699
References	2511
DOCUMENT CONTENTS	
Keywords Plus (ID)	220
Author's Keywords (DE)	304
AUTHORS	
Authors	199
Authors of single-authored docs	13
AUTHORS COLLABORATION	
Single-authored docs	14
Co-Authors per Doc	2.93
International co-authorships %	8.219
DOCUMENT TYPES	
article	66
article; early access	4
review	3

publications. The m-index is defined as H/n , where h is the h-index and n is the number of years elapsed since the scientist's first publication (Aria and Cuccurullo 2017).

Analysis of Authors

Out of 199 authors, 187 published one article, nine published two articles and three published three articles. The authors J. Black, N. Nawaz and P. van Esch stand out (Table 6). K. Chaitanya and V. Prikshat V. start in 2021 his first article, having published a new paper every year since their first published article.

Regarding the impact rate of these authors, Table 7 shows that once again, the authors J. Black, N. Nawaz and P. Van Esch have the highest index (h-index of 2), which is double the average of the other authors, i.e., 1.

The affiliation of the authors is diverse, as shown in Table 8. Two universities stand out from the rest, i.e., University of Turin, Kingdom University and Auckland University of Technology, with the highest number of articles of four, three and two each, respectively.

The publication of articles from diverse countries reflects the subject's global importance. Seventeen countries published papers related to the application of AI in HRM (Table 9). The countries with the highest number of publications were the USA, India and China, with 13, 9 and 8 articles, respectively.

Although New Zealand is not the country with the highest scientific research output, it stands out after USA (Table 10), because its articles have

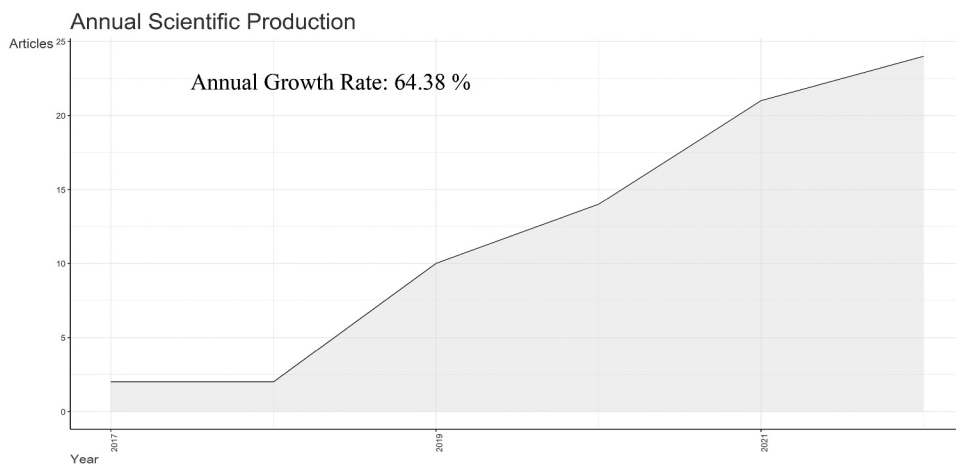


Figure 2. Annual evolution of publications.

Table 4. Sources with the largest number of related publications.

Sources	Articles
International Journal of Manpower	6
International Journal of Human Resource Management	5
Business Horizons	4
International Journal of Technology Management	3
Journal of Management Information and Decision Sciences	3
Advances in Developing Human Resources	2
Computers in Human Behavior	2
Ethics and Information Technology	2
International Journal of Scientific and Technology Research	2
Asia Pacific Journal of Human Resources	1
Benchmarking	1
BPA Applied Psychology Bulletin	1
California Management Review	1
Cyprus Review	1
Employee Responsibilities and Rights Journal	1
European Journal of Information Systems	1
Forum Scientiae Oeconomia	1
Frontiers in Psychology	1
Human Resource Management	1
Human Resource Management Review	1

the highest number of citations and therefore have the highest impact on the related scientific literature.

Analysis of Documents

The purpose of this study was to identify the most relevant and cited articles. [Table 11](#) shows how Dabirian et al. (2017) is the article with the highest number of total citations. It has been cited 89 times, with an average annual citation rate of 14.83 citations. These authors argue that as employees use information technologies to openly share and access work-related experiences across organizations,

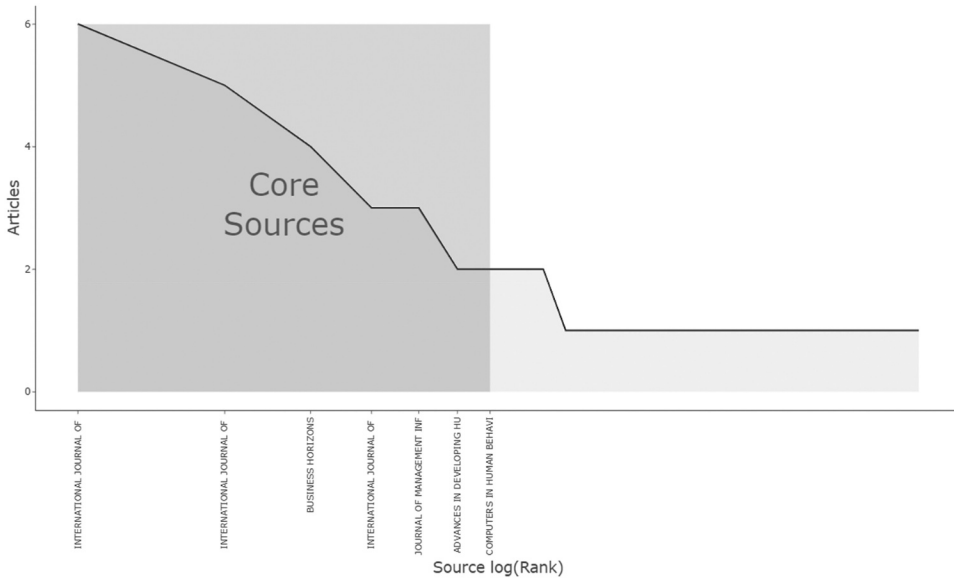


Figure 3. Bradford Law.

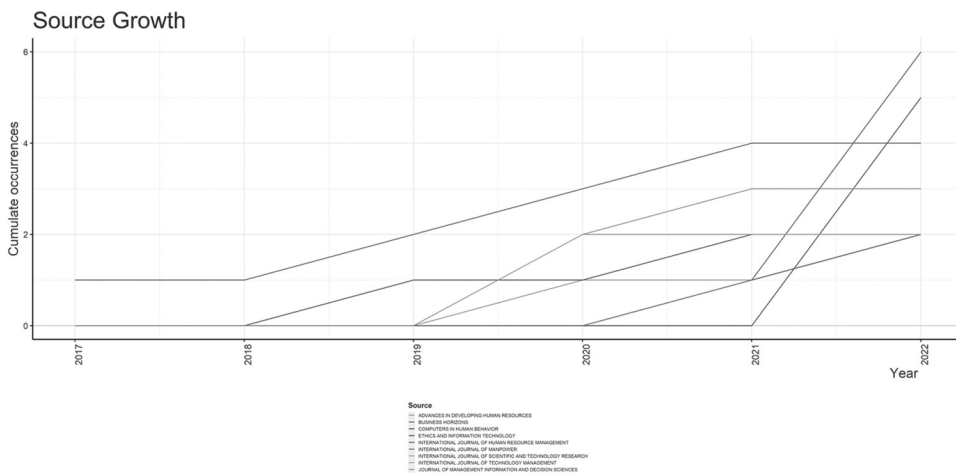


Figure 4. Source Growth.

their expectations and evaluations of workplaces change. Using a data collection of 38,000 reviews of the best and worst rated employers on Glassdoor, a crowdsourced online employer branding platform, they concluded that employers could use AI to become great workplaces that attract highly skilled employees.

Spectroscopic analysis: According to Marx et al. (2014), Reference Publication Year Spectroscopy (RPYS) is a quantitative method for identifying the historical origins of a research field. It creates a temporal profile of cited references for a set of papers, thus highlighting the period in which relatively

Table 5. Impact of sources.

Sources	h_index	g_index	m_index	TC	NP	PY_start
Business Horizons	3	4	0.5	138	4	2017
International Journal of Human Resource Management	3	5	3	87	5	2022
International Journal of Manpower	2	3	1	12	6	2021
International Journal of Scientific and Technology Research	2	2	0.667	14	2	2020
Journal of Management Information and Decision Sciences	2	2	0.667	4	3	2020
Advances in Developing Human Resources	1	1	0.333	2	2	2020
Asia Pacific Journal of Human Resources	1	1	0.5	4	1	2021
Benchmarking	1	1	0.333	12	1	2020
California Management Review	1	1	0.25	61	1	2019
Computers in Human Behavior	1	2	0.25	25	2	2019

TC: Total citations. PY_start: Year of publication start

Table 6. Relevant authors.

Authors (>=2 articles)	Articles	Articles Fractionalized
Black J.	3	1.50
Nawaz N.	3	2.33
van Esch. P.	3	1.50
Avrahami D.	2	0.50
Chaitanya K.	2	0.50
Chiappetta J. C.	2	0.45
Mcneese N.	2	0.45
Pessach D.	2	0.50
Prikshat V.	2	0.45
Schelble B.	2	0.45
Singer G.	2	0.50
Wang X.	2	0.67

Table 7. Author impact factor.

Authors	h_index	g_index	m_index	TC	NP	PY_start
Black J.	2	3	0.5	49	3	2019
Nawaz N.	2	2	0.667	4	3	2020
van Esch. P.	2	3	0.5	49	3	2019
Chulanova O.	1	1	0.25	5	1	2019
Abdeldayem M.	1	1	0.333	11	1	2020
Aggarwal V.	1	1	0.25	2	1	2019
Agrawal R.	1	1	0.5	1	1	2021
Aich A.	1	1	0.333	3	1	2020
Akar C.	1	1	1	2	1	2022
Akshay P.	1	1	0.333	1	1	2020

Table 8. Authors affiliations.

Affiliation	Articles
University of Turin	4
Kingdom University	3
Auckland Univ. Technol.	2
Clemson University	2
Coventry University	2
Lomonosov Moscow State University	2
Neoma Business School	2
Shandong University	2
University of Nicosia	2
University of Reading	2

Table 9. Scientific production by countries.

Country	Freq
USA	13
India	9
China	8
UK	4
New Zealand	3
Brazil	2
Denmark	2
France	2
Italy	2
Australia	1

Table 10. Average number of citations of articles by country.

Country	TC	Average Article Citations
USA	67	9.57
New Zealand	49	16.33
China	38	5.43
Italy	29	9.67
India	15	3.75
Denmark	7	3.50
Cyprus	6	6.00
UK	5	1.67
France	1	1.00
Poland	1	0.50

significant findings were published along with the temporal roots of a discipline.

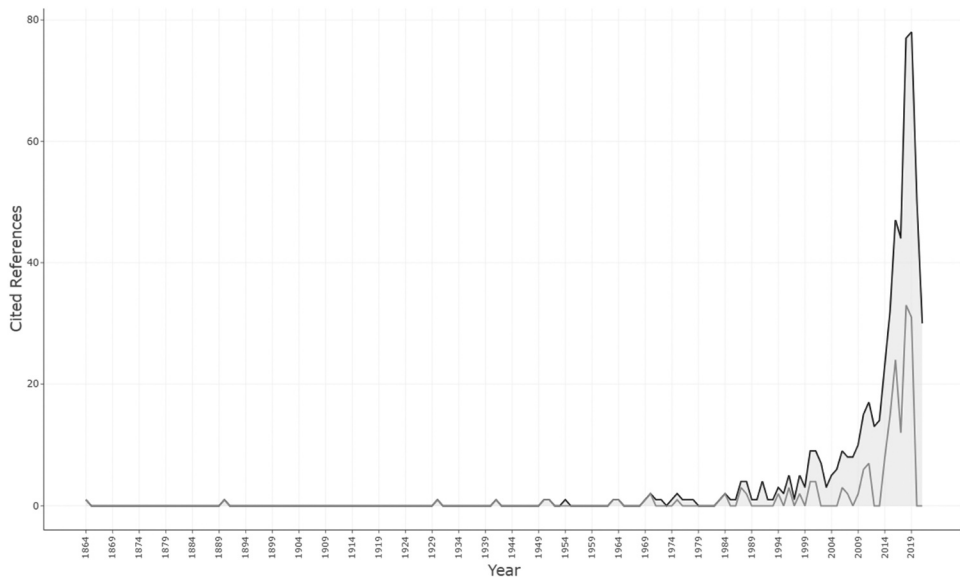
Figure 5 shows how AI as a technology and its use in HRM has evolved and its interest in publishing-related work has increased. Spectroscopic analysis began in 1980, when related publications started appearing, although as depicted in Figure 5, it was not until 2017 that there was a notable increase in the related scientific production.

The first upturn occurred in 2000, and disruptive technology gained widespread importance during the early 2000s. Ever since then, changes have been observed in how organizations operate and how HRs are managed (Minbaeva 2021). Until the early 1980s, 70–90% of the company's value was linked to tangible assets. However, since 2000, the value linked to intangible assets has increased to 65%, with people being the “cogs in the wheel of intangible assets” (Black and van Esch 2021). Two AI techniques are being used in HRM: fuzzy logic and artificial neural networks, both of which aid in the optimal workforce design and performance management.

The second upturn occurred in 2006 when knowledge management became a field of greater importance even though it was already being studied. Since intangible factors had already become more important, there was a greater need for HRM to obtain competitive advantages. Using data mining will be the

Table 11. Most cited articles.

Article (Authors/Journal)	Total Citations	TC Per Year
(Dabirian et al. 2017)/Business Horizons	89	14.83
(Tambe et al. 2019)/California Management Review	61	15.25
(Vrontis et al. 2022)/The International Journal of Human R. M.	51	51.00
(Caputo et al. 2019)/Management Decision	29	7.25
(Black and van Esch 2020)/Business Horizons	26	8.67
(Suen et al. 2019)/ Computers in Human Behavior	24	6.00
(van Esch and Black 2019)/Business Horizons	21	5.25
(Gupta et al. 2018)/Journal of Information Technology Teach Classes	17	3.40
(Malik et al. 2022)/The International Journal of Human R. M.	16	16.00
(Giermindl et al. 2022)/European Journal of Information Systems	14	14.00
(Pan et al. 2022)/The International Journal of Human Resource M.	14	14
(Pillai and Sivathanu 2020)/Benchmarking	12	4
(Abdeldayem and Aldulaimi 2020)/Internatio. J. of Scientific & T. R.	11	3.67
(Kong et al. 2021)/International Journal of Contemporary H. M.	9	4.5
(Arslan et al. 2022)/International Journal of Manpower	9	9
(Ogbeibu et al. 2022)/Journal of Intellectual Capital	9	9
(Michailidis 2018)/Cyprus Review	6	1.2
(Vinichenko et al. 2019)/International Journal of Recent T. and E.	5	1.25
(Sahota 2019)/IEEE Engineering Management Review	5	1.25
(Boustani 2022)/Journal of Asia Business Studies	5	5

**Figure 5.** Annual Spectroscopic Analysis of publications.

key to correctly assessing competencies and performance. Through these evaluations, it will promote the exchange of knowledge among employees, along with the generation of new ideas and business opportunities.

Finally, the greatest upturn occurred in 2018, since it is from this year that the study on AI being applied to HRM began gaining importance. The endless possibilities of AI automation generate interest in its application in HRM (Jatobá et al. 2019).

Keyword analysis: Keywords are essential for a bibliographic search. Their identification and analysis are crucial for gaining in-depth knowledge of the articles' content and the topics being analyzed.

The most impactful frequent keywords related to AI application in HRM are AI, HR, Management, and Machine Learning. The importance of the AI concept stands out, but to a lesser extent than that of HRM. AI is experiencing an increase in its application in various fields, but as far as HRM is concerned, it has not yet occurred completely.

Knowledge Structures Analysis

Conceptual structure: It refers to what the science is about, the main themes, and trends. Specifically, multiple correspondence analysis (MCA) helps analyze categorical data to reduce large sets of variables into smaller sets to synthesize the information in the data (Mori et al. 2014). To do this, the data are compressed into a low-dimensional space to form a dimensional or three-dimensional graph that uses planar distance to reflect the similarity between keywords.

Three clusters or groups of content are highlighted:

- (1) **Cluster 1 (AI in HRM):** In this first cluster, the AI tools being applied in HRM are addressed to highlight big data and machine learning. With big data, this might support decision-making processes, since large amounts of varied data from various sources can be quickly analyzed, resulting in a stream of actionable knowledge (Caputo et al. 2019). As for machine learning, the last decade has accelerated its use and applicability owing to the availability and variety of data (Hamilton and Davison 2022). This type of learning provides systems with the ability to learn (Soleimani et al. 2022) and mimic human skills (Bolander 2019). Machine learning can learn from the current context and generalize what it has learned to a new context. There are many organizations that, despite not comprehensively using AI in HRM, use this type of algorithm (Nankervis et al. 2021).
- (2) **Cluster 2 (Digital Recruitment):** It is the use of ICTs to attract potential candidates, keep them interested in the organization during the selection processes, and influence their employment choice decisions (Johnson et al. 2021). Pillai and Sivathanu (2020) point out how talent acquisition has become a crucial function for HR managers, with organizations going to great lengths to attract the best talent.

For van Esch and Black (2019), talent acquisition has changed from a tactical HR activity to a business priority. The basis of competitive

advantage has shifted from tangible assets to intangible assets, thereby increasing the strategic importance of human capital to make it the key driver. The shortage of talent in the labor market has intensified the need for human capital.

The traditional method of searching for candidates used to be a slow and costly process. However, today, due to technological advances and digital recruitment, it is much easier and cheaper. Furthermore, since nowadays most of society is spending increasing time in the digital space, if companies want to attract and recruit talent, they have to do it in that space (Black and van Esch 2021).

3) Cluster 3 (Electronic HR): This cluster presents a much more “futuristic” vision of HR which involves complete digitalization and the use of robots in daily functions.

While electronic HR management stands out in using technology to facilitate HRM processes like, recruitment, selection, training, performance management, human resource planning, compensation, etc. (Johnson et al. 2021). Through ICTs, it is possible to achieve better control of performance and over the employees’ behavior for greater strategic and effective management.

Using robots in HRM also stands out. Future forecasts are that in 20 years, robots will be in charge of making some analytical decisions that are now being made by human managers, while humans will continue to be in charge of tasks like creativity (Stanley and Aggarwal 2019).

Social structure: It shows how authors or countries are related in a research field; the most commonly used is the co-authorship network (Aria and Cuccurullo 2017). The authors who stand out for having the highest number of shared publications are Black & van Esch and McNeese & Schelble. In general terms, there is a high degree of cooperation between authors in the publication of articles, and very few publications are being written by a single author.

In terms of collaboration between countries, the USA is the country with the highest number of collaborations. Whereas with New Zealand and with France, it should be noted that collaboration with the first country is much greater than with the second. Also, there are other collaborations between Brazil and Portugal, China and the United Kingdom, Germany, and Norway-Tunisia.

Discussion

The research questions initially raised after the results were obtained and the studies analyzed can be answered as follows.

Q1: AI is not yet commonly used in HRM. However, its use has acquired greater relevance in the last five years, with 2021 being the year with the highest number of publications. Authors like Cappelli et al. (2019) assert

that the application of AI in HRM has not advanced as expected. Among the main barriers are: the complexity of HR phenomena, associated data challenges, equity and legal constraints, and employee reactions. Poba-Nzaou et al. (2020) states that even though the “Fourth Industrial Revolution” again highlighted the need for people to be at the center of organizations, it seems that HR departments remain unprepared to take advantage of this new opportunity. Nankervis et al. (2021) point out that as technology advances, it will be impossible for the traditional HRM approach to not advance as well; in fact, the forecast is that over the next decade there will undergo a significant change. However, any research article indicates that social entrepreneurship will use the opportunities of Industry 4.0 to optimize its processes until 2030, but will decline complete automation, using human intellect and AI at the same time (Popkova and Sergi 2020)

Q2: The results obtained show that the literature has largely focused on the analysis of the application of AI in personnel selection. Qamar et al. (2021) pointed out that, although AI is becoming increasingly important for HR, instead of trying to take advantage of this tool to apply it to the entire people management process, they focused only on a specific sub-area. It is meaningless to attract the best talent if you don't have the tools to manage it. As highlighted by Nankervis et al. (2021), the automation of certain complex processes will require increasingly highly trained and qualified personnel.

Q3. The reviewed literature highlights that most employees still do not welcome the application of AI in HRM. Nankervis et al. (2021) show that many HR professionals lack the necessary skills and competencies to meet the challenges of AI application in HR processes, hence their possible contrary attitude. Fritts and Cabrera (2021) highlighted the concern of HR professionals against the use of recruitment algorithms, as they can dehumanize the hiring process. Vinichenko et al. (2019) highlighted how many employees lacked confidence in the integrated use of machines in the management processes because they feared being replaced by machines. However, this is unlikely, since even if some tasks are fully automated, the human factor will not disappear completely (Johnson et al. 2021; Kong et al. 2021).

Q4. A company gaining a competitive advantage involves several factors like customer satisfaction through quality service, cost optimization, innovation, productivity, etc. The primary function of any technology, specifically AI, is to improve the efficiency and effectiveness of the HR function to help make recruitment, retention, and management easier and more accurate, automate repetitive tasks, and reduce labor costs (Nankervis et al. 2021). The innovation processes is a strategical practice in business companies (Bonilla-Chaves and Palos-Sánchez 2022)

All this will result in an innovative organization full of talent with high labor welfare, which will provide quality service to customers, obtain customer

satisfaction, and lead to higher productivity. It has also been observed that the use of AI helps predict staff turnover to avoid the reduction in productivity derived from it.

Theoretical Contributions

Our study contributes significantly to the literature on IA and HRM implications. It is noteworthy how we introduce the framework of previous research on AI and HRM. Through the results obtained by applying the methodology of bibliometric analysis and systematic review of the literature, it has been possible to ascertain the relative and insufficient attention by the academy to these two phenomena together.

Given the lack of similar studies applying bibliometric analysis in this field of study, it can be the first starting point on the same. This will help future researchers as a reference point for expanding and developing the content of this study. It can also be useful for those in HR who want to investigate and learn more about the subject and analyze the current situation to have a minimum number of references in case they want to enter this world.

Practical Contributions

Also important are the practical implications derived from the results of this work for the management and administration of organizations, specifically for HRM. The results obtained provide some very important ideas that can be of great use to HR managers and experts related to the area to understand what the main behaviors and trends have been so far when companies adopt HRM connected to IA.

As noted Pan et al. (2022), an important fact is a need for managers of organizations to encourage the development and implementation of specific resources in the field of AI in such a way that the adoption of AI in the company is favored.

Limitations and Future Research

This research work, like others, is also subject to a series of limitations. The main limitation has been marked by the dispersion of information and, sometimes, limited to particular issues that do not favor a general view of the topics in a connected way.

Research Agenda

Regarding the main lines of research derived from this work, it is important to highlight the relevance of conducting studies that focus not only on the

application of AI in the recruitment and selection of personnel, but also on the rest of the areas in HR management. It would also be opportune to conduct studies that analyze AI's effect on HRM in the employees of organizations.

Conclusions

The most relevant conclusions derived from the results obtained and their analyses are:

First, there has been an extraordinary development in technology in recent years, especially AI. Despite its development, importance of its impact in the HRM field has not been as expected. AI application in HRM is a very specific field of study, since most of the research has focused on its application in the recruitment and selection of personnel, besides important functions like training, development, or personnel rotation. There is indeed an increasing interest in talent and the recruitment of highly qualified personnel, which is necessary for facing the changing environment and high competition. But it should be noted that talent must not only be found, but also maintained and developed to turn it into a competitive advantage. For this reason, it is essential to use AI technologies in other functions and extract the maximum added value from each process.

Second, based on the results obtained, it can be seen that there are still fears and negative feelings in HR employees and managers about the AI application. These feelings can complicate or slow down the use of AI in this area. Although technology has strongly disrupted the labor market and has helped create new businesses and develop existing ones, it has also eliminated many others, thus causing greater concern. But it should be noted that AI technologies need people for their proper management. Despite being faster, working 24 hours a day, optimizing time and tasks, etc., AI does not have the essential soft skills for any work environment.

Like any new technology, AI has its strengths and weaknesses. This makes it essential for HR departments to carry out an effective AI implementation strategy to integrate it safely within organizations, thus eliminating the potential damage. It is obvious that in the long term, the use of disruptive technologies will no longer be optional but rather necessary to remain competitive among other organizations; otherwise, they will lose their market positions or worse, will disappear.

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EMERGING AMBIDEXTROUS OPPORTUNITIES: HOW MALAYSIAN GLCS CAN LEVERAGE ARTIFICIAL INTELLIGENCE

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ABSTRACT

Government-linked companies (GLCs) are integral to Malaysia's economic growth, operating under substantial government ownership and control across various sectors. In the digital era, it is crucial for GLCs to adopt advanced technologies, particularly artificial intelligence (AI), to enhance their performance and remain competitive against non-GLCs. This study investigates the role of AI in GLCs to provide ambidextrous opportunities, addressing the research gap focused on AI adoption and potential impact in Malaysian GLCs. A Systematic Literature Review (SLR) was conducted using the PRISMA method to analyze 48 peer-reviewed articles from the Web of Science (WOS) and Scopus databases, published between 2013 and 2024. The results revealed various roles of AI that can be leveraged by GLCs as ambidextrous opportunities, including automating financial tasks and services, enhancing transparency in procurement, optimizing supply chain resources, improving public administration, strengthening policy governance, optimizing marketing efforts, enhancing human resource management, boosting corporate readiness, optimizing energy management, managing sustainable natural resources, revolutionizing healthcare, implementing smart farming, enhancing e-commerce strategies, optimizing renewable energy utilization, enhancing smart grid management, increasing organizational agility, developing managerial skills, enhancing product development, and improving manufacturing efficiency. The study provides managerial recommendations for integrating AI across various sectors, aiming to boost competitiveness, operational efficiency, and innovation. This research contributes to the literature by offering practical insights and strategic guidance for policymakers and managers in leveraging AI to create ambidextrous opportunities, ensuring sustained growth and competitiveness in the digital age. This study recommends future research focus on the issues and challenges of leveraging AI in GLCs.

Keywords: *Artificial intelligence, government-linked companies, ambidextrous opportunities, digital transformation, adoption, systematic literature review, technology*

1. INTRODUCTION

Government-linked companies (GLCs) are companies where the majority is owned by the government through its shares, agencies, or holding entities. These are commercial enterprises but are subject to significantly higher government ownership and control. GLCs can be partially or fully owned by the government and operate in different sectors of the economy [1-3]. GLCs are a major part of the Malaysian economy, making significant contributions to gross capital formation and Gross Domestic Product (GDP). They are important in sectors such as energy management and

construction, natural resource management, healthcare, energy and power, agricultural, energy and environmental management, e-commerce, public administration and governance, education, financial services, supply chain and logistics, marketing, banking and financial, public service, and manufacturing, ensuring stability and sustained economic growth [2].

GLCs have been benchmarked and proven to have improved their performance, particularly after the government's transformation initiatives [4]. However, GLCs still underperformed in terms of performance and profits compared to non-GLCs [5].

Non-GLCs are usually more market-oriented and competitive than GLCs. This is due to the legacy structure and government collaborations of GLCs, which impact their competitive pursuits in both domestic and international markets [6].

Some GLCs are actively engaged in adopting current technologies, whereas others might still lag behind in technological development. More than a decade ago, Wong and Govindaraju [7] points out that the GLCs such as Proton and Golden Hope exhibited significant technological advancements, whereas TNB lacked the necessary technological development to enhance performance. This evidence proved that the technology become important factor to enhance the GLCs performance.

Moreover, the utilization of artificial intelligence (AI) in the private sector enhances private companies' performance, enabling more businesses to compete in the market and improve profitability [8]. AI refers to intelligence demonstrated by machines and is one of the sub-fields of computer science. These tasks encompass learning, reasoning, problem-solving, perception, and natural language processing. Machine learning, deep learning, and other sophisticated computational techniques simulate human cognitive functions using AI technologies [9, 10], in order to derive higher performances by organizations and greater efficiencies within a competitive market [8, 11].

Additionally, AI can offer organizations ambidextrous opportunities to achieve better performance and efficiencies [12-15]. Ambidextrous opportunities refer to the set of favorable conditions for organizations that allow them to exploit what currently exists while exploring new possibilities, which quite often lead to potential benefit, advantage, or gain. Exploration, for instance through new experimentations and market entries, can be said to be the opposite of exploitation. Often described as efficiency enhancement and operation optimization, the two have to find a good strategic balance. Organizational ambidexterity is the construct in organizational theory that is critical to maintain competitiveness and promote innovation [15]. Sourcing ambidextrous opportunities can create long-term performance, evolve to meet new challenges and take advantage of increasing possibilities, promoting long-term performance and resilience [16]. For instance, Korhonen, et al. [17] advance an abstract concept of ambidextrous usage of AI in a policing context. In police departments, enables the development and research of new

technologies for predictive policing, in which AI algorithms are used to analyze data and make forecasts about possible criminal activities with a view to preventing crimes before they are committed. Additionally, AI could improve contemporary methods of data analysis by enabling processing large volumes of data using the police, thereby increasing efficiency and productivity in both decision-making and resource allocation [17].

Based on the Resource-Based View (RBV), a competitive advantage can be obtained from a firm's resources and capabilities. In the context of GLCs, AI could carry strategic importance in the way of operational efficiency and innovation [18]. This theory seeks to explain the differences between firms that maintain a competitive advantage and those that do not, though it often overlooks variations in performance within individual firms [19]. Essentially, the RBV analyzes the role of a firm's tangible and intangible resources in creating and sustaining competitive advantage [20].

Despite its tremendous potential, AI capabilities are lacking in GLCs, leading to limited ambidextrous opportunities [21]. Therefore, it is important to investigate the role of AI in GLCs so that these companies can leverage AI as ambidextrous opportunities, ultimately supporting their growth and competitiveness in the digital age. The ambidexterity could achieve both innovative initiatives and operational efficiencies to increase GLCs performance [22]. Leveraging AI can increase performance in this competitive market, ensuring they are not left behind in the AI age. While private companies are beginning to adopt AI and experience its benefits, there is a gap in research on AI adoption and its impact on Malaysian GLCs. To date, there are limited studies focused on the adoption and potential impact of AI in GLCs, as previous studies tend to focus on general AI adoption or specific industries without addressing the unique context of GLCs. This study will focus on answering the following research questions (RQs):

RQ1: What is the role of artificial intelligence (AI) that can be leveraged in Malaysian government-linked companies (GLCs)?

RQ2: What is the role of artificial intelligence (AI) in enhancing ambidexterity in Malaysian government-linked companies (GLCs) to improve both existing operations and foster innovation?

Through answering these RQs, this study contributes to the existing literature by filling a gap

in understanding AI adoption and its potential impact on Malaysian GLCs. For policymakers and managers, it offers valuable insights on harnessing AI to enhance competitiveness, productivity, and long-term economic resilience. The research is very useful for giving practical recommendations that enable GLCs to advance their competencies with ambidextrous opportunities of exploration and exploitation toward continuous improvement and competitiveness in the era of digitalization.

2. METHODOLOGY

This study conducted a Systematic Literature Review (SLR) following the methodology of Preferred Reporting Items for Systematic Reviews and Meta-Analyses. The SLR process addressed the research questions (RQs) to identify the role of artificial intelligence (AI) that government-linked companies (GLCs) could leverage to enhance ambidextrous opportunities. The PRISMA process is shown in Figure 1.

2.1 Search Methods

Artificial intelligence (AI) has been well recognized for its advances and has taken place from the year 2013 [23]. The implementation of AI has significantly increased from 2013 onwards, leading to greater research interest in the field. The role of AI in organizations has become more prominent after 2013 [24].

Therefore, this SLR focused on peer-reviewed journal articles and conference papers published between 2013 and 2024. It was conducted using electronic databases accessible through the authors' university library system. The databases used in this SLR from the university library system were Web of Science (WOS) and Scopus. This study targeted articles about AI implementation in organizations across various sectors.

This SLR fulfilled all of the following inclusive criteria:

- Must include the keywords: Artificial intelligence, government-linked companies, ambidextrous opportunities, digital transformation, adoption, systematic literature review, technology

- Must be written in the English language
- Must be peer-reviewed journal articles and conference papers that discuss about the role of AI
- Must be available from electronic databases accessible through the authors' university library system
- The timeframe of the article from 2013-2024

This SLR excluded all of the following exclusive criteria:

- Written in a language other than English
- The papers written not in the timeframe of 2013-2024
- Not indexed and peer-reviewed in WOS and Scopus databases
- Not included the keywords: Artificial intelligence, government-linked companies, ambidextrous opportunities, digital transformation, adoption, systematic literature review, technology

2.2 Sample

A total of 7,065 articles were found in the WOS and Scopus databases. After removing 3,470 duplicate studies, 3,595 articles remained. These 3,595 articles were then filtered, and 1,156 were excluded based on the inclusion and exclusion criteria mentioned above, resulting in 2,439 articles eligible for inclusion. Out of these, some included terms that did not fulfill the criteria of this study. The author then removed the articles that did not focus on the role of AI in GLCs or similar organizations in Malaysia, leaving 48 articles published in peer-reviewed journals eligible for this SLR.

The research categorized these 48 journals based on their areas of focus, which were engineering (n = 5), policy (n = 2), diagnostics (n = 1), energy (n = 2), economics (n = 4), government (n = 2), sustainability (n = 1), public health (n = 1), chemistry (n = 1), human resources (n = 1), science (n = 3), physics (n = 1), complexity (n = 1), artificial intelligence (n = 6), training and development (n = 1), applied economics, finance and accounting (n = 1), management (n = 4), administration (n = 1), technology (n = 7), innovation (n = 1), business (n = 1), and foresight (n = 1). Table 1 provides the list of journals included in this SLR.

Table 1: Database and journals included in systematic literature review

Database	Journal	Frequency
	Engineering Applications of Computational Fluid Mechanics	1

Web of Science (WOS)	Resources Policy	1
	Diagnostics	1
	Mathematical Problems in Engineering	1
	Renewable and Sustainable Energy Reviews	1
	Energy Reports	1
	International Journal of Social Economics	1
	Transforming Government: People, Process and Policy	1
	Sustainability	1
	Frontiers in Public Health	1
	Technological Forecasting and Social Change	1
	18th IEEE International Colloquium on Signal Processing and Applications (CSPA)	1
	TrAC Trends in Analytical Chemistry	1
Scopus	AIP Conference Proceedings	1
	Asia Pacific Journal of Human Resources	1
	Asia-Pacific Social Science Review	1
	Circular Economy	1
	Complexity	1
	Discover Artificial Intelligence	2
	European Journal of Training and Development	1
	Foresight	1
	Government Information Quarterly	1
	IAES International Journal of Artificial Intelligence	1
	International Conference on Computing, Communication, and Intelligent Systems, ICCIS 2023	1
	International Journal of Advanced Science and Technology	1
	International Journal of Applied Economics, Finance and Accounting	1
	International Journal of Data and Network Science	2
	International Journal of Electrical and Computer Engineering	1
	International Journal of Information Management	1
	International Journal of Intelligent Networks	1
	International Journal of Public Administration	1
	International Journal of Sustainable Construction Engineering and Technology	1
	Journal of Advanced Research in Applied Sciences and Engineering Technology	1
Journal of Information Systems Engineering and Management	1	
Journal of Open Innovation: Technology, Market, and Complexity	1	
Journal of Theoretical and Applied Information Technology	1	
Lecture Notes in Networks and Systems	2	
	Management Review Quarterly	1
	Problems and Perspectives in Management	1
	International Conferences on WWW/Internet 2018 and Applied Computing 2018	1
	Research in World Economy	1

Scopus	Review of Applied Socio-Economic Research	1
	Science and Public Policy	1
	Sinergie Italian Journal of Management	1
	Vision The Journal of Business Perspective	1

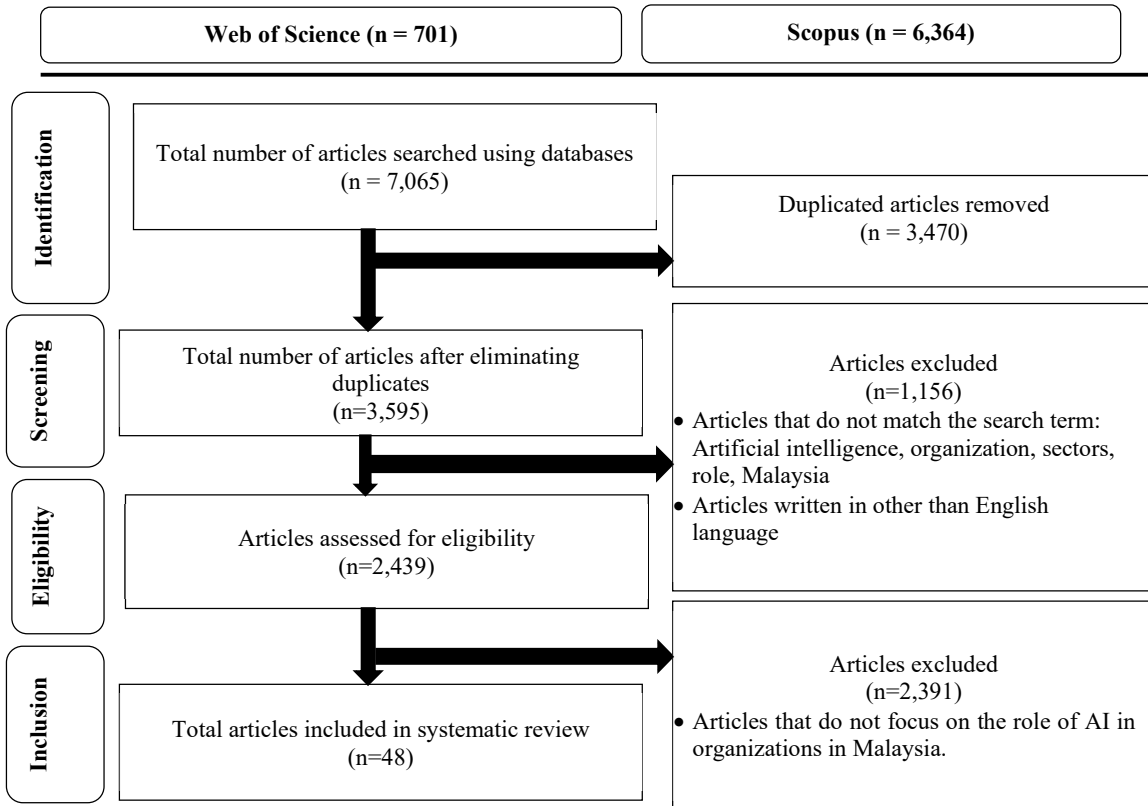


Figure 1: PRISMA flow diagram

3. RESULT & DISCUSSION

This section is structured into three parts, each addressing different research questions. The first research question examines how artificial intelligence (AI) can be utilized in Malaysian government-linked companies (GLCs), while the second explores how AI can enhance ambidexterity to improve current operations and drive innovation. Part A discusses the various roles AI can play across different sectors within GLCs, emphasizing its potential to boost productivity and innovation in strategic management, customer interactions, operations optimization, and new revenue generation, directly addressing the first research question. Part B investigates how AI can create ambidextrous opportunities for GLCs by balancing exploration and exploitation, promoting sustained growth and competitiveness, thus addressing the

second research question. Part C provides managerial recommendations for integrating AI across various sectors, predicts the expected outcomes, and highlights the importance of AI in improving competitiveness, operational efficiency, and innovation, offering guidance for policymakers and managers to leverage AI for continuous progress in the digital era.

3.1 Leveraging Artificial Intelligence (AI) in Malaysian Government-Linked Companies (GLCs)

This Systematic Literature Review (SLR) identified the role of artificial intelligence (AI) that could be leveraged in Malaysian government-linked companies (GLCs). The findings represent the role of AI among GLCs in various sectors, such as energy management and construction, natural resource management, healthcare, energy and power,

agriculture, energy and environmental management, e-commerce and business performance, public administration and governance, education, financial services, supply chain and logistics, finance and accounting, marketing, banking and finance, policy governance, management and operations, public service, human resource management, and manufacturing, as shown in Table 2.

GLCs could leverage AI to boost productivity and innovation in every sector, from strategic management and customer interaction to operations optimization and new revenue generation. [25]. Further, it enhances data-driven decision-making and organizational efficiency for strategic planning and operation management, and decision support in strategic planning [26]. Moreover, AI can be applied for organizational performance improvement in process innovation, personal expertise development, and enhancement of organizational structure in general [27]. For example, organizational strategic planning can also be done with the use of AI, but this should be balanced with traditional methods. This emphasizes the important for companies to consider their level of maturity in terms of AI and introduce adaptive policies to make it possible for the company to integrate AI in general [28]. Indeed, AI has an important influence on business success because talent acquisition and development systems, along with performance management, are improved [29]. Besides, AI allows for efficiency in financial and accounting activities to be achieved by savings in time, smooth operations, and the use of advanced technologies to a greater extent [30]. In the procurement and compliance sectors, AI can enhance transparency, accountability, and eliminate corruption in public procurement processes [31]. Additionally, in the economic planning and workforce development sector, AI supports decision-making, streamlining of operations, and a knowledge base to better understand the expected labor market changes and skills needs [32]. Besides that, in the commercial sector, AI may be involved in boosting business functions, problem-solving, and offering up-to-date feedback with customized functions based on customer preferences [33]. In the management and operational sector, GLCs can use AI to effectively develop managerial skills, organizational performance, innovative processes, and readiness for advanced technologies. This could in essence result in cost savings, better competitive

advantages, and improved economic outlook for the country [34]. Similarly, AI help guarantee enhanced agility, flexibility, and resilience in face of economic alterations [35].

On the other hand, GLCs may optimize the use of AI in the human resource management sector to help in augmenting capabilities in employee development, recruitment, training and overall HR skills [36]. In turn, this will drive the enhancement of better HR planning, employee retention, recruitment processes, and overall HR efficiency for organizations [37]. Additionally, AI can be applied to GLCs to enhance human resource training in some development and workforce skills, developing careers, and realizing competitive workforce sustainability [38]. Furthermore, AI could enhance corporate readiness as well as perceptual gain and technological readiness, ultimately improving the effectiveness of the HR system [39]. It could also reinforce HR capabilities, increase employee satisfaction levels, and support more sophisticated, data-based, predictive employee retention strategies, enhance recruitment, talent management, HR operations, learning and development, reporting, analytics, and self-service support [40, 41].

AI can be used to predict cooling loads in residential buildings for the energy management and construction sectors by GLCs, thereby improving energy efficiency. AI is also utilized for optimizing energy consumption and designing energy-efficient buildings [42]. In the natural resource management sector, AI can significantly influence policy-making, decision-making, and sustainable resource use [43]. Additionally, AI can be deployed within the e-commerce divisions of GLCs to optimize digital strategies and enhance competitive positioning in the market [44].

In the management of energy and the environment, AI can be utilized by GLCs for better use of renewable energy and to help achieve the United Nations SDGs for sustainable development [45]. Moreover, AI can further be adapted to the learning sector of GLCs in order to improve teaching practices, enhance access to education, and infuse intelligent learning and social robots into the system [46]. Additionally, AI in the financial service sector of GLCs can further be utilized in automated investment management services, customer

engagement, and services' automation that boosts robo-advisor acceptance, as well as covering perceived risks through security measures and strategic endorsements [47, 48]. Moreover, it will drive efficiency and create operational improvements in the form of automation, which reduces costs and enhances decision-support services to make manual work on dull, time-consuming activities [49].

Within the supply chain and logistics industry, GLCs could use AI for better resource optimization, enhance the overall decision-making process, and address security and system complexity issues to increase speed and efficiency in operations, among others [50]. Further, the adoption of AI technology in the marketing space can potentially provide a way forward to increase effectiveness while moving towards digital marketing strategies within the GLCs, enhance user engagement, improve resource allocation, and support data-driven decision-making [51].

More importantly, AI could be used within the public service sector in GLCs to drive citizen satisfaction through better procedural justice and higher private value creation and, consequently, toward greater perceived usefulness and enjoyment of public services [52]. Equally, the GLCs could maximize AI in that sector to manage the risk posed and underpin the regulatory frame in a more resilient manner such that the challenges and opportunities of the AI technology sectors like politics, economy, and culture are tackled, as expressed [53].

In the healthcare sector, GLCs could leverage AI in various ways. In this regard, the transformational power of AI, especially ChatGPT, in healthcare cannot be overlooked. AI can improve patient care, support medical professionals, enhance pandemic control, and facilitate medical education and research [54]. Most importantly, it can be used for earlier cancer detection, better targeting for treatment personalization, and commercializing the new innovative diagnostics technologies [55]. AI can also improve emergency management, the maintenance of patients' records, diagnostics, and the overall delivery of health, while it resolves issues related to trust, security, privacy, and precision in care provision [56].

Additionally, AI can be applied by GLCs for those in the energy and power segment. The energy sector is one of the primary focuses for AI application, particularly in system control and automation to the development of future policies regarding sustainability and efficiency in the use of energy in GLCs across Malaysia [57]. Furthermore, this will enhance the accuracy of electric load demand forecasting, resulting in high operation efficiencies and low costs in smart grid management [58].

Through AI, the GLCs in the agriculture industry could perform smart farming for the revamping of agriculture, enhancement of productivity, and optimization of economic results [59]. All these are potential through a better-optimized technique of smart farming brought about by the acquisition of AI. These can facilitate enhanced decision-making and those issues relating to food scarcity and sustainable growth, efficiency in rice production, secured food supplies, and better livelihoods of the farmers [60, 61]. In the agriculture sector of GLCs, AI has an application to the precision agriculture approach for improved crop management, better resource use efficiency, and sustainable farming practices [62]. AI may further be extended to the monitoring of soil and crops, managing diseases, and productivity in order to manage soil and crops for overall productivity in a better way, which makes the practice of farming more sustainable and efficient [63].

Furthermore, GLCs could leverage AI in the public administration and governance sector to enhance administrative efficiencies, improve governance practices, and test new AI-based structures and applications [64]. In the public administration sector, AI could improve citizen services, enhance operational efficiency, streamline interactions through chatbot adoption, enhance decision-making processes, and support the adoption of data intelligence and analytics [65, 66]. It can also be used to further enhance the productivity and quality of service in GLCs' public administration sector by addressing AI adoption issues toward realizing inclusive development and creating new opportunities for management alignment, cultural integration, infrastructure development, data management, and ethical governance [67].

AI in banking and finance will enable the GLCs to provide security, operational efficiency, create confidence among consumers, innovate with new financial products and services, and above all improve customer segmentation, credit risk analysis, fraud detection, and business intelligence [68, 69]. Besides that, AI can improve quality services by applying ChatGPT on performance expectancy and technology readiness increasing the possibility to adopt new systems and remain competitive in marketplace [70].

GLCs could leverage AI in the manufacturing sector. New product development and innovation would be enhanced by AI, which, in the long run is going to result in higher product success and increased companies' growth [71]. It could further advance the cause by seeking support in operational efficiency, innovation, and competitive advantage from AI, with a sharp emphasis on top management and government support [72].

3.2 The Role of Artificial Intelligence (AI) In Providing Ambidextrous Opportunities in Malaysian Government-Linked Companies (GLCs)

The Systematic Literature Review (SLR) was carried out to identify the possible roles and opportunities for artificial intelligence (AI) that the government-linked companies (GLCs) can leverage within its sectors. The results show that AI serves as a powerhouse that drives productivity and innovation while leading GLCs to high levels of both. This SLR proposes managerial recommendations which GLCs can use to create ambidextrous opportunities balancing exploration and exploitation for sustained growth and competitiveness as shown in Table 3.

The integration of AI analytics tools into decision-making by strategic management and innovation will strengthen the processes of decision-making and open up ambidextrous opportunities among GLCs to have real actionable and predictive intelligence for strategic decisions [73]. Use of such tools may result in overall organizational efficiency leading to improved strategic planning and operational management, which has been suggested as a use case in striking balance between exploration and exploitation activities [26]. With the backing of AI-based analytics, GLCs would capitalize on

insights from the market, customers, and performance operations in ways that could empower the making of smart, data-driven decisions for strategic and operational impact. Besides, fostering process innovation through strategic management and innovation is necessary to cultivate a culture of constant improvement and adaptability. The embedding of AI in process management systems allows for the detection and correction of inefficiencies, thereby supporting continuous innovation through the process [74]. In an AI-driven optimized process, not just an increase in productivity is observed but also a culture where creativity and innovations are enhanced. This dual approach supports ambidexterity where GLCs will be able to explore new opportunities but yet improve their existing processes to ensure they stay competitive in dynamic markets [27].

GLCs should automate routine financial jobs, such as invoicing, expense tracking, and financial reporting, to bring up operational efficiency with AI-enabled accounting software [75]. This would lead to a reduction in costs and an increase in details in parts tracking, thereby resulting in precise financial decision-making for the organization to balance exploratory and exploitative activities [30]. It is important to add more transparency to the procurement processes. The AI software should monitor all transactions, requisitions, and purchases made within the procurement system for compliance and efficiency [76]. This will effectively raise the aspect of transparency, accountability, and bring down corruption. Thus, it will boost overall operational efficiency and breed an ambidexterity-friendly organizational atmosphere [31].

Another major area, in this context, involves creating ambidextrous opportunities for the GLCs by optimizing supply chain resources through AI. In this AI is to be used in logistics and any other supply chain applications to help GLCs in better decision-making and handling security issues, besides improving operational efficiency [77]. Through AI, huge data caches can be processed to predict demands, control stocks, and improve routings, eventually allowing a degree of efficiency and effectiveness that greatly improves supply chains. Both exploiting the current methods and exploring new supply chain solutions ensure the balance of this

duo, which is meant for sustained competitiveness [50].

AI can be very useful in governance and public service, greatly improving the efficiency of operations and satisfaction among citizens. Some of its most important applications are the use of AI chatbots in public administration for public inquiries and the application of AI data analytics in policy-making [78]. This can help further better citizen service, quicker operations, and support for data-driven governance [65]. In addition, enhanced policy governance by introducing AI models for assessing the impacts of policies and facilitating regulatory compliance for dealing with risks and increasing regulatory frameworks [79]. Such an approach will ensure that GLCs would be able to strike a fair balance between a policy development need-driven innovation exercise and effective provision for regulatory oversight to underpin the ambidextrous opportunity [53].

The GLCs are made fit for financial services through the use of AI-driven financial advisory and customer service platforms. This enhances automated investment management using AI and improves customer engagement with the adoption of robo-advisors [47, 48, 80]. This will help improve service delivery while allowing for properly executed maintenance and customer personalization using new services. AI can be used in the domains of customer segmentation and targeted marketing and can drive digital marketing strategies more effectively in marketing. AI-enabled resource allocation and campaign optimization should be able to help GLCs get better outputs and wider customer engagement through ambidexterity [51, 73]. This will enable the GLCs to be ambidextrous, to be innovative with new marketing approaches and, concurrently, make optimum use of those strategies proved in research.

Enhancement of human resource management is another major factor that will enable such ambidextrous opportunities in GLCs. AI-based HR platforms will consequently increase HR efficiencies within the GLCs to hire, train, and manage performance for employee development and retention [36, 81]. These are the AI tools that shall convert any human resource function into a more effective and responsive activity pertaining to the

needs of an organization and its employees. Moreover, it even doubles the corporate readiness through amplified corporate readiness, heightened perceptual gains, and greater technological readiness by utilizing AI tools to track the performance of employees to facilitate growth in their career path [39, 82]. The dual enhancement of HR function, in the present condition and preparing the firm for future challenges helps to create ambidexterity as the two critical elements are balanced, short-term needs with long-term strategic aims.

It is also key that AI is responsible for managing energy; therefore, optimizing energy management is necessary to achieve ambidextrous opportunities. AI-enabled smarter energy management at residential and commercial buildings can automate control and monitor cost-saving measures to increase energy efficiency and minimize operational costs [42, 83]. Additionally, AI can help in real-time climate and resource monitoring, optimize land management for cattle and humans so that policymakers and scientists have more data available for decision-making and better resource management for sustainable use and preservation [43, 84].

The use of AI in diagnostic tools, patient management systems, and medical research platforms can enhance patient care, aid healthcare providers in their practice, and contribute to the advancement of medical research [54, 85]. AI is revolutionizing health care, with the means to detect disease early, diagnose disease, predict outcomes, and personalize treatment across numerous diseases, whether they are of the oncological, neurological, or cardiological type [86]. Moreover, AI may help clinicians make diagnostic and predictive decisions, and utilize personalized medicine approaches [87].

In agriculture, AI can increase the productivity of farmers, optimize resource utilization, and accomplish all the sustainable objectives through AI-deployed sensors and drones for precision farming and crop monitoring [59, 88]. In the same manner, the use of AI in the customer relationship management (CRM) and digital marketing platform can improve digital strategies for competitive positioning and engaging more customers, respectively, while also impacting e-commerce strategies that favor the GLCs [44, 89].

Increased use of renewable energy, supporting energy and environmental sustainability, can only benefit GLCs if AI is deployed in green energy projects to help in better resource conservation [90]. The other development that AI can bring is achievement in sustainable development goals (SDG) and driving sustainable solutions [45] with AI-based improvement in the management of smart grids. This will involve AI predictions for managing energy-distribution optimization loads to help in the increment of operational efficiency and reduction of cost associated with the same respect [58, 91]. These challenges can be addressed by the application of AI in the management of the smart grid, enabling it to predict loads and manage the optimization of energy distribution. The measures complement ambidextrous opportunities of GLCs to pilot new solutions to energy while making an efficient use of resources.

Ambidextrous opportunities are brought to achievement levels by increasing the agility of the organization. The use of AI for the GLCs to simulate economic scenarios and develop strategic responses in enhancing further in agility, flexibility, and resilience in managing economic dynamics is suggested as an opportunity [35, 92]. Moreover, the building up of managerial competencies with the help of AI algorithms that facilitate managerial training and innovation workshops will support the innovative process, cost reduction, and readiness toward advanced technologies [34, 93]. Such practices focusing on the improvement of current management practices and preparing for challenges in the future foster ambidextrous opportunities and balance the tensions between immediate operational needs and long-term strategic development.

As we gain more opportunities to be ambidextrous in manufacturing, resources and desires will turn to product development enhancement [94]. A greater success rate in product innovation with AI indicates increased growth in GLCs [95], where the AI can be targeted toward fast and effective product development that is capable of solving the needs in the market. AI solutions in operational research further play facilitating roles, such as optimized solutions for smart factories with integrated AI capabilities to enhance the production processes [96]. In manufacturing, the capacity of AI

in automation of the production process and reduction of waste while increasing product quality holds the potential to be a game-changer in terms of operating efficiencies, innovation, and competitive advantage [72]. This two-prong approach to develop existing methods together with the exploration of uncharted production territories allows ambidextrous options and balances immediate operational needs with future-proof developmental strategies.

Based on the literature reviewed until now, this study posits that the application of AI might enable Malaysian GLCs to develop ambidextrous capabilities to create opportunities for both innovation and operational efficiency that boost their competitive position and relate positively to the growth and viability of the economy.

3.3 Practical/Managerial Implications

Table 3 delineates the significance of artificial intelligence (AI) in various sectors, providing managerial recommendations for its integration, and predicting the anticipated results. Within the context of strategic management and innovation, AI bolsters decision-making capacities [26] through integrated analytics tools, facilitating improved strategic planning and operational effectiveness [26, 73]. Moreover, the integration of AI in process management fosters a continuous cycle of innovation and productivity enhancements, cultivating an environment conducive to innovation [27, 74].

In financial and operational efficiency, AI-powered accounting software automates financial operations, thereby improving efficiency and decision-making processes [30, 75]. Furthermore, AI enhances transparency and minimizes corruption in procurement procedures by consistently monitoring transactions [31, 76].

Regarding managerial and operational flexibility, AI increases the organization's flexibility and further develops managerial competencies within the organizational unit [34, 35, 92, 93]. Besides, AI enhances manufacturing through refining product innovation as well as operational effectiveness [71, 72, 95, 96].

Table 3 also contains a variety of sector-specific applications, which cut across from optimizing supply chain resources using AI [50, 77], to enhancing public administration through AI chatbots and data analytics [65, 78], and reinforcing policy governance through the use of AI models [53, 79]. In finance and marketing, investment management and customer interaction are enhanced by AI, and in the process, it maximizes efforts in marketing through the segmentation of customers in financial services and marketing [47, 48, 51, 73, 80].

In HR and organizational capacities, AI-driven platforms streamline HR effectiveness and corporate readiness [36, 39, 81, 82]. AI also streamlines energy administration [42, 83], advocates for sustainable natural resource management [43, 84], and transforms healthcare via sophisticated diagnostic mechanisms and patient management frameworks [54, 85-87].

In agriculture, AI sustains intelligent farming practices [59, 88], whereas in e-commerce, it enriches the management of customers' relationships and digital marketing strategies [44, 89]. Lastly, under energy and environmental sustainability, AI maximizes the use of renewable energy and the management of smart grid systems [45, 58, 90, 91]. All these roles and recommendations for AI are efforts to create ambidextrous opportunities for the government-linked companies (GLCs) that would synchronously align exploration and exploitation for sustainable growth and competitiveness.

Overall, the application of AI-based analytics tools in GLC management will improve the efficacy of strategic decision-making and operational efficiency through quick actionable and predictive intelligence [73]. The incorporation of process management systems with AI could then lead to the detection and remediation of inefficiency while fueling constant innovation [74]. Besides that, it helps in increasing efficiency and accuracy in invoicing, tracking expenses, and reporting finances by deploying AI accounting software [75].

AI can be used by the managers of GLCs as a tool to monitor, for both efficiency and compliance, all the procurement transactions [76]. Moreover, the usage of AI can apply in logistics to optimize the application of supply chain in GLCs [77]. In addressing public inquiries as well as policy formulation, AI chatbots and data analytics will be instruments of enrichment [78], while AI models that are shared in evaluation can be utilized for impacts on policies and regulatory compliance [79]. AI-driven advisory and customer service platforms will help ramp up engagement and service automation in financial services [80].

In the marketing domain, GLCs' managers will be able to utilize AI tools for customer segmentation and directed efforts [73]. AI-enabled HR platforms make hiring, training, and performance management easier [81], as AI tools themselves can monitor the performance and career development of an employee [82]. In the energy sector, GLCs managers may optimize energy management within the buildings and support green energy projects using AI [83, 90]. For real-time monitoring of the natural resources, they could also utilize AI to assist in the sustainable management [84].

In healthcare, managers within GLCs could apply AI in diagnostic tools, patient management, and medical research [85]. For agriculture, GLC managers can deploy AI sensors and drones to ensure precision farming [88]. Finally, CRM and digital marketing platforms in GLCs could be run through AI toward improvements in strategy in customer engagement [89], (Wan et al., 2021; Zhang et al., 2021), even using AI for smart grids in load forecasting and optimization in energy distribution for better efficiency [91]. AI may also simulate economic scenarios for strategic answers and boost managerial training and innovation workshops [92, 93]. AI implementation in product innovation and development as well as in smart factory optimized solutions manufacturing can be utilized by GLCs managers in the manufacturing sector.

Table 2: The Role of Artificial Intelligence (AI)

No	Author (Year)	Sectors/Operations	The Role of Artificial Intelligence (AI)
1	Zheng, et al. [42]	Energy Management and Construction	Optimize energy consumption and improve the design of energy-efficient buildings.
2	Pandey, et al. [43]	Natural Resource Management	Enhance decision-making, optimize resource use, and create strategies for sustainable management.
3	Younis, et al. [54]	Healthcare	Enhance patient care, support medical professionals, improve pandemic management, and facilitate medical education and research.
4	Singh, et al. [55]		To improve early cancer detection, personalize treatment, and facilitate the commercialization of innovative diagnostic technologies
5	Akhtar, et al. [56]		Improve emergency management, patient record maintenance, diagnostics, and overall healthcare service delivery
6	Islam and Ahmed [58]	Energy and Power	Enhance electric load demand forecasting accuracy
7	Danish and Senjyu [57]		enhance system operations, control, automation, and policy development for a sustainable and efficient energy future.
8	Huo, et al. [61]	Agricultural	Enhance smart farming methods, refine decision-making processes, and tackle issues related to food shortages and sustainable development.
9	Javaid, et al. [62]		Implement precision agriculture, improve crop management, enhance resource utilization, and support sustainable farming practices
10	Rodzalan, et al. [59]		Essential for implementing smart farming to revitalize agriculture, enhance productivity, and optimize economic outcomes.
11	Sarkar, et al. [63]		Enhance soil management, crop monitoring, disease management, and overall productivity, promoting sustainable and efficient farming practices
12	Zaman, et al. [60]		Promote smart farming practices, improve rice production efficiency, ensure food security, and enhance the well-being of farmers
13	Hannan, et al. [45]	Energy and Environmental Management	Optimize renewable energy utilization and support the attainment of sustainable development goals.
14	Fonseka, et al. [44]	E-commerce	Optimize digital strategies and enhance competitive positioning in the market
15	Jais and Ngah [66]	Public Administration and Governance	Improve citizen services, enhance operational efficiency, and streamline interactions through chatbot adoption
16	Di Vaio, et al. [65]		Enhance decision-making processes, improve efficiency, and support the adoption of data intelligence and analytics
17	Alshahrani, et al. [67]		Improve productivity, service delivery, address the AI adoption issues

18	Wirtz, et al. [64]		Uplift administrative efficiencies, improve governance practices, and test new AI-based structures and applications.
19	Ahmad, et al. [46]	Education	Enhance teaching methods, improve access to education, and implement intelligent learning systems and social robots.
20	Al-Gasawneh, et al. [47]	Financial Services	Enhance investment management, improve service automation, and address perceived risks through security measures and strategic endorsements
21	Zheng, et al. [48]		Enhance automated investment management services, improve customer engagement, and drive the adoption of robo-advisors.
22	Khaled AlKoheji and Al-Sartawi [49]		Boost operational efficiency, lower costs, and support decision-making, to transform repetitive and time-intensive manual processes.
23	Isnin, et al. [50]	Supply Chain and Logistics	Optimize resources, facilitate better decision-making, and resolve security and system complexity challenges leading to faster and more efficient operations
24	Rahim, et al. [51]	Marketing	Increase the effectiveness of digital marketing strategies, increase user engagement, improve resource allocation, and support data-driven decision-making.
25	Bouteraa, et al. [70]	Banking and Financial	Increase service quality by using ChatGPT, improve performance expectancy, enhance technology readiness by enabling the adoption of new systems and staying competitive in the market.
26	Kalyani and Gupta [68]		Offer security, drive operational efficiency, create consumer confidence, and innovate financial products and services.
27	Raúl, et al. [69]		Improve customer segmentation, credit risk analysis, fraud detection, and business intelligence.
28	Wang, et al. [52]	Public Service	Drive citizen satisfaction through better procedural justice and higher public value creation.
29	Yee and You [53]		Manage risk, strengthen regulatory frameworks, ensuring the challenges and opportunities from the AI technology disrupting sectors.
30	Jianjun, et al. [71]	Manufacturing	Enhance new product development and innovation
31	Ghani, et al. [72]		Improve its operational efficiency, innovation, and competitive advantage with a strong focus on top management and government support.
32	Abonamah and Abdelhamid [25]	Various operations/sectors	Improve productivity and innovation of strategic management, customer interactions, operations optimization, and new revenue generation.

33	Adobor and Yawson [31]	Enhance transparency, accountability, and also eliminate corruption in public procurement.
34	Usmani, et al. [26]	Enhance data-driven decision-making and organizational efficiency.
35	Sharif Ismail and Muhammad [27]	Improve the overall organizational performance
36	Ghosh, et al. [32]	Assist in decision-making, streamline operations, and build a knowledge base on the anticipated labor market impacts and skills requirements from AI adoption.
37	Costa, et al. [33]	Improve business functions, problem-solving, as well as to provide a real-time response and customized function based on customers' preferences
38	Muala, et al. [28]	Enhance organizational strategic planning
39	Xin, et al. [29]	Influence on business success.
40	Rawashdeh, et al. [30]	enhance their efficiency, save time, and increase the adoption of advanced technologies in financial and accounting operations.
41	Odeibat [34]	Develop managerial skills, enhance organizational performance, support innovative processes, and provide readiness for advanced technologies.
42	Ciampi, et al. [35]	Increased agility, flexibility, and resilience when faced with economic changes
43	Laviola, et al. [36]	Improve capabilities of employee development, recruitment, training, and overall HR skills.
44	Siradhana and Arora [37]	Enhance HR planning, employee retention, recruitment processes, and overall HR efficiency.
45	Hamouche, et al. [38]	Strengthen employee skills training, career development, and create a more sustainable, competitive workforce.

46	Agarwal [39]	Various operations/sectors	Enhance corporate readiness, perceptual gains, and technological readiness.
47	Zhang and Jamil [40]		Improve HR functionalities, increase employee satisfaction rates, and allow advanced data-driven and predictive employee retention strategies.
48	Sithambaram and Tajudeen [41]		Improve recruitment, talent management, HR operations, learning and development, reporting, analytics, and ultimately, self-service assistance.

Table 3: The Role of Artificial Intelligence (AI) In Providing Ambidextrous Opportunities in Malaysian Government-Linked Companies (GLCs)

Sectors	The Role of Artificial Intelligence	Managerial Recommendation	Expected Outcome
Strategic Management and Innovation	enhance decision-making capabilities [26].	AI-based analytics tools need to be integrated to get immediate actionable and predictive intelligence to make strategic decisions [73].	This will enable better strategic planning, operational management, and improve organizational efficiency [26].
	promote process innovation [27].	Embed AI into process management systems to detect and remediate inefficiencies while enabling ongoing innovation [74].	AI-driven process improvements can enhance productivity and create a culture of innovation [27].
Financial and Operational Efficiency	automate financial tasks [30]	Deploy AI-driven accounting software for tasks such as invoicing, expense tracking, and financial reporting [75].	This will boost efficiency, reduce costs, and support more accurate financial decision-making [30].
	enhance transparency in procurement [31].	AI software should constantly monitor all requisition and purchase transactions from an outside vendor for compliance and efficiency via the procurement system [76].	AI can enhance transparency, accountability, and reduce corruption in procurement processes [31].
Supply Chain and Logistics	optimize supply chain resources [50]	Deploy AI logistics and other AI supply chain applications [77].	AI can facilitate better decision-making, resolve security challenges, and improve operational efficiency [50].
Public Services and Governance	improve public administration [65]	Use AI chatbots for public inquiries and AI data analytics for policy-making [78].	AI can enhance citizen services, operational efficiency, and data-driven governance [65].
	strengthen policy governance [53]	Creating AI models to evaluate policy impacts and facilitate regulatory compliance [79].	AI can help manage risks and strengthen regulatory frameworks in various sectors [53].
Financial Services and Marketing	automate financial services [47, 48]	Deploy financial advisory and customer service platforms powered by AI [80].	AI can provide automated investment management, enhance customer engagement, and increase the adoption of robo-advisors [47, 48]
	optimize marketing efforts [51].	Use AI in customer segmentation and targeted marketing efforts [73].	AI can increase the effectiveness of digital marketing strategies and improve resource allocation [51].
HR and Organizational Capabilities	enhance human resource	Employ AI-powered HR platforms for hiring, training, and performance management [81].	AI can improve HR efficiency, employee development, and retention [36].

	management [36]		
	boost corporate readiness [39]	Use AI tools to monitor employee performance and for career growth [82].	AI can enhance corporate readiness, perceptual gains, and technological readiness [39].
Energy and Environmental Sustainability	optimize renewable energy utilization [45]	Include AI in green energy projects for effective management of resources [90].	AI can support the attainment of sustainable development goals (SDGs) and promote environmental sustainability [45].
	enhance smart grid management [58]	Load forecasting and energy distribution optimization on smart grid systems using AI [91].	AI can improve operational efficiency and reduce costs in energy management [58].
Management and Operational Flexibility	increase organizational agility [35]	Simulate economic scenarios and develop strategic responses using AI [92].	AI can enhance agility, flexibility, and resilience in response to economic changes [35].
	develop managerial skills [34]	Algorithms emerging as augmentation of managerial training and innovation workshops [93].	AI can support innovative processes, cost reduction, and readiness for advanced technologies [34].
Manufacturing Innovation	enhance product development [71]	Use AI in product innovation and development [95].	AI can lead to greater product success and organizational growth [71].
	improve manufacturing efficiency [72]	Manufacture optimized smart factory solutions with AI capabilities [96].	AI can improve operational efficiency, innovation, and competitive advantage [72].
Sector-Specific Applications	optimize energy management [42]	Use AI for smarter energy in residential and commercial buildings and automate control and monitor money-saving opportunities in energy management systems [83].	This will enhance energy efficiency and reduce operational costs [42]
	sustainable natural resource management [43]	Measure and monitor natural resources in real time, using AI to determine the true cost of resources; for use as an input for new policies and decisions—utilizing AI for better management of natural resources [84].	AI can promote sustainable resource use and support environmental conservation efforts [43].
	revolutionize healthcare [54]	Implement AI in diagnostic tools, patient management systems, and medical research platforms [85].	AI can improve patient care, support medical professionals, and facilitate advanced medical research [54].
			AI is revolutionizing healthcare by enhancing early detection, diagnosis, treatment, and outcome prediction in various diseases, including cancer, neurology, and cardiology [86].
			AI can support physicians in diagnosis, disease prediction, and treatment customization [87].
	implement smart farming [59]	Precision farming and crop monitoring through AI-deployed sensors and drones [88].	AI can enhance productivity, optimize resource use, and support sustainable agricultural practices [59].
enhance e-commerce strategies [44]	Incorporate AI into customer relationship management (CRM) and digital marketing platforms [89].	AI can optimize digital strategies, enhance competitive positioning, and increase customer engagement [44].	

4. LIMITATIONS

In terms of limitations, this systematic literature review (SLR) is constrained by the PRISMA methodology used to search for articles. The search was conducted electronically using only the available sources of the authors' university library system, which are WoS and Scopus. Still, another limitation is that this study is narrowed to peer-reviewed articles written in the English language only with the specific date of publication from 2013-2024. Lastly, generalizability and scope were at its limit since this study focused only on the articulation of artificial intelligence (AI) that can be adapted by Malaysian government-linked companies (GLCs).

5. CONCLUSION

Government-linked companies (GLCs) could be identified as those firms with significant government ownership that have remarkably contributed to the economic growth of Malaysia. Today, in this digital market, GLCs should consider adopting current technology within the digital domain in order to improve their performance and compete at the same level as non-GLCs. One main digital technology is artificial intelligence (AI), which hugely enhances performance in this competitive market.

However, there is still a lack of using AI in GLCs. This may be a reason for lagging in this competitive market. Therefore, this study would like to understand the role of AI in enhancing the ambidextrous opportunities among Malaysian GLCs for their growth and competitiveness in the digital era. This paper has identified the role of AI that can be leveraged by GLCs to enhance ambidextrous opportunities through the SLR. The current paper contributes to filling such a gap as the scant work available on the adoption and impact of AI in Malaysian GLCs tends to be either focused on general AI adoption or in certain industries without addressing the unique context of GLCs.

Derived from the findings, the research has identified a number of functions for AI, such as automation of financial processes, ensuring transparency in procurement, optimization of supply

chains' resources, betterment in public administration, enhancement in policy governance, automation of financial services, optimization of marketing endeavors, perfection of human resource management, increase in corporate readiness, energy management, sustainable natural resources management, revolutionizing healthcare, implementation of smart farming, e-commerce strategies, optimization of renewable energy utilization, smart grid management, increase in organizational agility, development of managerial skills, product development, and improvement in manufacturing efficiency. These roles of AI are recommended in this study for implementation in the specific sectors of GLCs to enhance their ambidextrous opportunities.

Moreover, this study provided managerial recommendations for implementing AI in various sectors of GLCs, which can significantly boost their competitiveness and ensure sustained growth in the digital age. GLC managers could integrate AI-based analytics, embed AI in process management, deploy AI-driven accounting software, utilize AI for monitoring procurement and optimizing logistics, enhance public inquiries and policy-making with AI chatbots, improve financial services with AI advisory platforms, use AI for marketing customer segmentation, streamline HR functions with AI-powered platforms, optimize energy management, employ AI for sustainable resource management, implement AI in healthcare diagnostics, enhance precision farming with AI sensors and drones, improve CRM and digital marketing strategies, optimize smart grids, simulate economic scenarios for strategic responses, and drive product innovation and smart factory solutions in manufacturing. Future studies could focus on the issues and challenges that may arise from leveraging AI in GLCs.

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TEAM COMMUNICATION AND TASK EFFICIENCY**

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Abstract. At a time when digital transformation is reshaping work processes and how companies approach and perform tasks, artificial intelligence (AI) is emerging as a vital element of this evolution. AI-powered tools are changing how companies interact with customers and fundamentally impacting internal processes and how they assign tasks to teams. This trend raises questions about the efficiency with which humans and AI perform assigned tasks and the potential implications for future workplace dynamics. The main objective of this study is to provide a deeper understanding of the differences in task performance efficiency between humans and AI and to identify optimal ways in which these two resources can be used together to maximize their potential in the modern workspace. Through a comprehensive methodology and range of research methods, the paper offers both theoretical and practical benefits for academics, management practitioners and AI developers. Through this approach, the article expands the academic discourse on task performance effectiveness in the AI era. It provides strategic insights for organizations seeking to effectively leverage AI alongside human resources.

Keywords: Artificial Intelligence (AI); task efficiency; human - AI collaboration; digital transformation; teamwork and productivity; ai in workplace; task assignment strategies; management; communication; content

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1. Introduction

Today's economy is undergoing dynamic development, with industry digitalisation being one of the most significant trends. This shift requires businesses and organisations to adopt new technologies and develop strategies for effective interaction between workers and digital tools. Artificial Intelligence (AI) plays a crucial role in this transformation as it becomes the centre of new methods of management, communication, and decision-making (Angelova, Stoyanova and Stoyanov, 2023). The integration of AI into everyday work processes not only changes the configuration of social and economic relations but also opens new opportunities for increased efficiency and innovation in all sectors (Palos-Sánchez et al., 2022; Tugui et al., 2022; Giraud et al., 2023; Androniceanu, 2023).

The arrival of artificial intelligence (AI) has revolutionized many industries, and the field of human resource management is no exception. Artificial intelligence is changing how businesses, companies and organizations conduct HR activities and develop their work teams. AI is now a common part of an individual's daily life and work environment (Kim, Jang and Kim, 2022). One of the primary roles of artificial intelligence, which also hides its colossal potential, is the collection and analysis of data. Nowadays, this is mainly used in marketing to

collect and interpret customer preferences and data or analyze resumes in recruitment (Angelova Stoyanova and Stoyanov, 2023).

Empirical studies show that integrating AI into business processes positively impacts business performance, increases levels of creativity, and contributes to a more efficient and inclusive workforce (Su, Togay and Côté 2021; Burnett and Lisk, 2019). However, at the same time, there are concerns about data privacy and AI's potential replacement of human labour (White and Lidskog, 2022). These challenges highlight the need for a balanced approach to AI implementation that considers its potential and its use's ethical aspects.

In the context of these changes and challenges, this paper focuses on analysing the effectiveness of human task performance compared to artificial intelligence. This paper brings new perspectives on the possibilities of collaboration between humans and AI in work processes. Through this approach, we aim to enrich the academic discourse on the use of AI, to provide managers and executives with practical guidelines for improving work efficiency, and to contribute to the ethical and sustainable development of technology in business. The study relies on a comparative analysis of the performance of "HOW" type tasks between human teams and AI systems, emphasizing qualitative assessment of their performance, adaptability, and innovation potential. Through this paper, we offer a new perspective on the future direction of the use of AI in the world of work and the place that humans will occupy in it.

2. Task assignment

Task assignment is a sub-element of management. The literature agrees that the essential criteria that should be clearly defined when assigning a task include the desired outcome, time horizon, responsibility for performance, available resources, and specification of what is considered successful completion of the task (Pechová, Volfová and Jírová, 2023). According to Plamínek (2009), expressing support and creating space for questions and discussion is also an important point, as understanding the assigned task is considered the basis for future success and acceptance. In some ways, a well-managed process of defining the work task and the associated responsibilities can optimize the worker's approach to the assigned work from the beginning (Kriek, 2019).

Without setting a goal, the task could not exist. The question remains, however, to what extent it is also necessary to determine how it is to be achieved. In this case, the preferences of each taskmaster/leader/manager are radically different (and usually closely related to the management style chosen), as are the preferences of each executor/subordinate/employee (Kamei and Markussen, 2022). Some need rigid structures and roles to achieve results, the presence of which reduces uncertainty, ambiguity, and misunderstanding. On the other hand, others may be demotivated by such an approach (Delfgaauw, Dur and Souverijn, 2020).

The "HOW" or process type of assignment mainly specifies how the performer's work will be done. It includes an enumeration or direct description of working methods. Yet, it is burdened with frequent control and consultation, as a result of which the assignor can manage only a small number of performers, and his work becomes less effective (Plamínek, 2009; Parkes, 2016).

In "WHAT" type assignments, we encounter a more autonomous approach; only the outcome to be achieved and the evaluation criteria are specified.

The paper's current title focuses on the "HOW" type of task assignment performed by members of the working team from Škoda Auto Vysoká škola o.p.s. and Škoda Auto a.s. and AI systems such as Chat GDP, Copilot Edge, Midjourney nao Bing AI or Alphabets Bard. The "WHAT" type of task assignment, associated with autonomous access and creativity, would not yet be handled correctly by AI systems. AI systems still need and will likely need specific types of information to process the task (Galanos, 2019). This paper compares the results of the implemented task to those acceptable to humans and AI systems.

This paper also works with data from a survey conducted by the authors in 2023 with 388 respondents and draws on the following data:

In the 2023 survey, when given a "WHAT" type task, 20.6% of respondents felt they had enough information to complete the task. 79.4% of respondents, on the other hand, lacked additional information in the task assignment. The following types of information were the most frequently identified by respondents (in order of response frequency):

- Information on the exact date, agenda, focus and objective,
- specific location of the venue,
- what is the deadline for completing the task,
- the priority of the task,
- the reason or purpose for performing the task,
- information on whether the task is confidential or public
- and a thank you or appreciation of the task.

58.8% of the respondents would find a specific procedure guide easier to complete the task, 41.2% did not require a guide to complete the task. At the same time, 58.8% of the respondents perceived the task as creative and 23.7% of the respondents ranked the task type as medium level of creativity. The remaining respondents rated the task as routine. 69.3% of the respondents believed they had all the skills and abilities to complete the task, 30.9% had only some skills, and 5.2% believed they did not have the skills and abilities to complete the task. Respondents felt that the following skills (in order of frequency) were necessary for completing the task:

- Good interpretation of information,
- good knowledge of grammar and stylistics,
- graphic skills,
- the art of motivation in written text
- and imagination (Pechová, Volfová, Jírová, 2023).

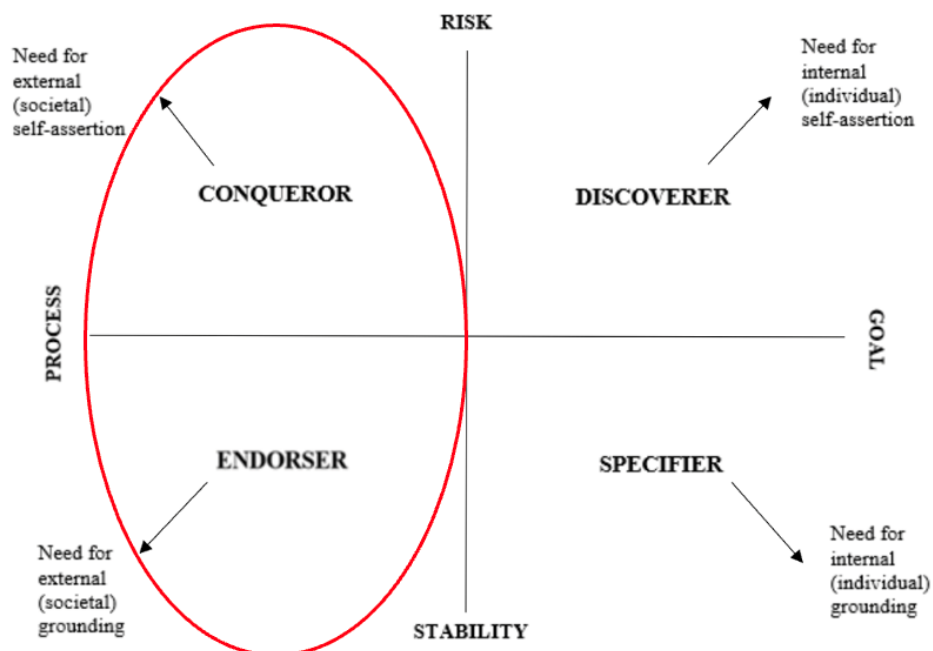


Figure 1. People preferring task type "HOW"
Source: the authors

3. The importance of AI

The way AI is perceived is closely related to whether the author considers it an existential threat to workers or even human existence or whether it is seen as a tool that can help people improve our society and living conditions (Galanos, 2019; Schwesig et al., 2023). There are beliefs that AI will evolve in ways that are harmful to jobs and society as a whole (White and Lidskog, 2021). On the contrary, analysts who see AI as a useful but not at the same time omnipotent technology stress that it will remain a tool that requires human intervention to be truly useful (Griva et al., 2023).

There are several perspectives on AI and the resulting definitions, e.g., machine-oriented view or human-oriented view, etc.; for this paper, the general perspective is drawn, i.e., that AI is the ability of artificial machines to emulate and simulate human methods for deductive and inductive knowledge acquisition and application and inference (Griva et al., 2023).

Chapter 3.1 characterizes selected AI systems, and Chapter 5. 2 presents the results and evaluation of the "HOW" task performed by AI systems.

3. 1 AI Systems

A key element of all AI systems introduced subsequently is natural language processing (NLP), which deals with the interaction between computers and human language. In practice, this means the ability to understand input queries, commands or context and respond with appropriate answers (Vithayathil and Nauroth, 2023). To achieve this goal, techniques and algorithms are used to analyse and understand text, recognise patterns and generate responses. These techniques include machine learning, deep learning, statistical methods and others.

Artificial intelligence based on NLP, be it chatbots, automatic translators, speech recognition software or sentiment analysis, is trained on datasets and huge amounts of textual data from various sources, be it books, newspapers, internet articles or even discussion forums and more. Thus, different language patterns and structures are learned. This training also occurs during the actual use of the application, which therefore adapts to the changing needs and trends in language and communication (Vithayathil and Nauroth, 2023; Vrontis et al, 2022).

ChatGPT

ChatGPT is a language model that is capable of generating text, answering questions, and leading controversies based on input data. ChatGPT uses deep neural networks to process natural language and was trained with reinforcement learning using human feedback (Farazouli et al., 2023).

Luke et al. (2024) report that in its first five days of existence, ChatGPT surpassed the one million registered users mark, making it the fastest-growing service on the Internet. Costa-Dookhan et al. (2024) state that NLP is one of the most important AI technologies, as most of the data we have around us is in the form of text. NLP is also widely used today to automate communication with customers using dialogue boxes on websites - the so-called chatbot. Landim et al. (2022) state that these virtual employees can recognize what the customer is asking, advise or suggest solutions to the problem 24 hours a day, and once programmed, the company does not have to incur any additional costs.

ChatGPT can write essays in hundreds of languages, compose celebrity-style speeches, summarize documents, write code, learn from previous exchanges, answer entertainment questions, or pass legal and medical exams (Kikalishvili, 2023).

However, the most significant threats associated with using this tool include the inability to identify real and reliable sources, errors in basic facts and reasoning, or the generation of misinformation. At the same time, it is also still possible to bypass ethical measures and guidelines when working with ChatGPT (Adeshola and Adepoju, 2023).

Bing AI

Bing AI is also known as Bing Chat or Copilot Edge. Bing Chat is a possible revolutionary tool that answers some of the problems of its biggest competitor, which is ChatGPT. The most significant difference is that the Bing chatbot has access to the Internet, so it can answer questions about current events. It also provides footnoted links to sources and can even format them as academic citations when asked (Bhardwaz and Kumar, 2023).

The Bing chatbot was originally in a limited pre-testing mode while Microsoft tested it with the public, and there was a waiting list that those interested in early access could join. Today, it is freely available and integrated into the Microsoft Edge web browser as part of the Bing search engine.

Alphabet's Bard

In the case of Alphabet, a chatbot called Bard is a search engine companion that uses Google's extensive LaMDA language model, making it similar to ChatGPT. Alphabet describes Bard as an 'experiment' and although it threatens to fall behind Microsoft in the race for chatbots, Alphabet claims it is implementing Bard in a 'responsible' way. The Bard question entry window even warns users that it is an experiment and may provide inaccurate or offensive answers (Waisberg et al., 2024).

Bard is not yet massively promoted. It has a separate website, and under each of its replies, there is a button that allows the user to leave the chatbot and use the Google search engine (Waisberg et al., 2024).

MidJourney

MidJourney is an independent research lab that explores new media of thought and expands the imaginative capacities of the human species (MidJourney, MidJourney, undated). MidJourney, like DALL-E or Stable Diffusion, generates images based on natural language descriptions, called "prompts," in English (Bhardwaz and Kumar, 2023).

The images generated at MidJourney are now of such high quality that they have raised controversy and questions about both the future of art and fairness. For example, one user entered and won an art competition with a generated image, which sparked substantial controversy. There are also comics based on images generated from MidJourney, which have raised copyright discussions. Again, therefore, ethical issues arise (Aiumtrakul, 2023)

DALL-E

DALL-E and DALL-E 2 are machine learning models developed by OpenAI to generate digital images based on descriptions. DALL-E consists of two neural networks; one is GPT, and the other is VQ-GAN. DALL-E 2 uses another development of OpenAI - CLIP - Contrastive Language-Image Pre-training artificial vision system (Comparative Text-Graphic Training). The system learns from hundreds of millions of images and their descriptions, learning to distinguish "how much" of text fragment X correlates with image X. That is, instead of predicting which image this description is more appropriate for, the artificial vision model studies exactly how this text and this image are related. Comparison instead of prediction allows CLIP to make connections between textual and visual representations of the same meaning. CLIP defines and creates semantic links between text and images (Aiumtrakul et al., 2023).

Due to ethical and security concerns, DALL-E access was restricted to pre-selected users for research insight. As of 2022, DALL-E 2 is available to anyone and the waiting list requirement has been removed; users can generate a certain number of images for free and can purchase more.

4. Methodology of research surveys

This paper focuses on investigating the effectiveness of task assignment and performance in work teams, with a particular emphasis on comparisons between humans and artificial intelligence systems. We build on previous research examining task assignments' impact on teamwork effectiveness and extend this theory by adding a new dimension - AI integration. The earlier paper, IMPACT OF TASK ASSIGNMENT ON EFFECTIVENESS IN

WORK TEAMS, develops a theory of task assignment of the "HOW" type, evaluates its effectiveness in work teams, and compares it with the effectiveness of tasks performed by AI. According to Svozilova (2016), a task is part of a complex activity; we can specify a desired outcome for it, and it has a relatively short duration. A manager can choose from two options when assigning tasks and assigning them to specific performers (Pechová, Volfová, and Jírová, 2023).

The main goal of our study is to compare the efficiency of "HOW" tasks, which are characterized by their specific instructions and procedures, between human teams and AI. To this end, we set two sub-objectives: first, to identify the key factors that influence the efficiency of task performance by human teams, and second, to assess how AI systems perform these tasks compared to humans.

A combination of quantitative and qualitative methods was used to answer these questions. First, a focus group survey was conducted in January 2024, involving students of ŠKODA AUTO University o.p.s. and employees of ŠKODA AUTO a.s., preferring the "HOW" method of assigning the task. At the same time, identical tasks were given to AI systems, including ChatGPT, Copilot Edge, Midjourney and Bing AI, to compare their effectiveness with human teams.

In the final stage, task performance was evaluated using the criteria of effective work performance. This evaluation was carried out with a target group of Škoda Auto a.s. managers who provided an assessment of task performance by both human teams and AI systems. The results of this evaluation and the facilitated workshop discussions with the executives offer deeper insights into the dynamics of task performance in the modern work environment and open further discussion on the role of AI in task assignment and performance.

This approach allowed us to comprehensively explore how task performance differs between human and AI teams and identify the factors that influence these differences. The methods and techniques used, including focus groups and executive evaluation, provided us with a robust dataset from which we could thoroughly analyse and interpret the differences in effectiveness we found.

The study's methodology was designed to ensure the validity of the findings. The selection of participants for the focus group was made based on their experience and preferences in the assignment of "HOW" type tasks, ensuring the data's relevance and representativeness. At the same time, the set of AI systems that were tested was carefully selected to reflect the wide range of tools available and their ability to perform the specific tasks assigned.

The analysis of focus group data and the evaluation by managers was conducted using both qualitative and quantitative analytical methods. This combination allowed us to quantify differences in effectiveness and explore in more depth the motivations, practices, and challenges that participants experienced during task completion. This methodology provides a comprehensive framework for exploring and understanding the dynamics of task performance effectiveness in an environment where the boundaries between human and artificial intelligence are blurring.

4.1 Target group

The target group for the focus group was carefully selected to reflect the wide range of positions and specialisations within the organisation of ŠKODA AUTO a.s. and ŠKODA AUTO University o.p.s., allowing for a comprehensive view of the interaction between humans and AI in task performance. The focus group consisted of both Škoda Auto College students and Škoda Auto employees. This group was further differentiated by gender, age and field of study or work specialisation to ensure that the results were representative of a wide range of work styles and preferences, all according to the results of previous research (Pechová, Volfová and Jírová, 2023). Respondents were divided into two main age categories: 22-25 years and 36-39 years, which allows us to compare attitudes and approaches to AI between the younger generation, who enter the labour market with up-to-date knowledge of digital technologies, and the middle generation, who have extensive work experience. In terms of study and work specializations, respondents were represented in three main areas: HR (Human Resources Management), SM (Sales Management) and LQ (Logistics and Quality Management), as

these are the specializations and work focuses that prefer to handle "How to" type tasks. This selection reflects the diversity of job roles and tasks within the organization. It allows us to understand better how different types of tasks and job requirements affect the effectiveness and adoption of AI. The target group can be seen in Fig. 2.

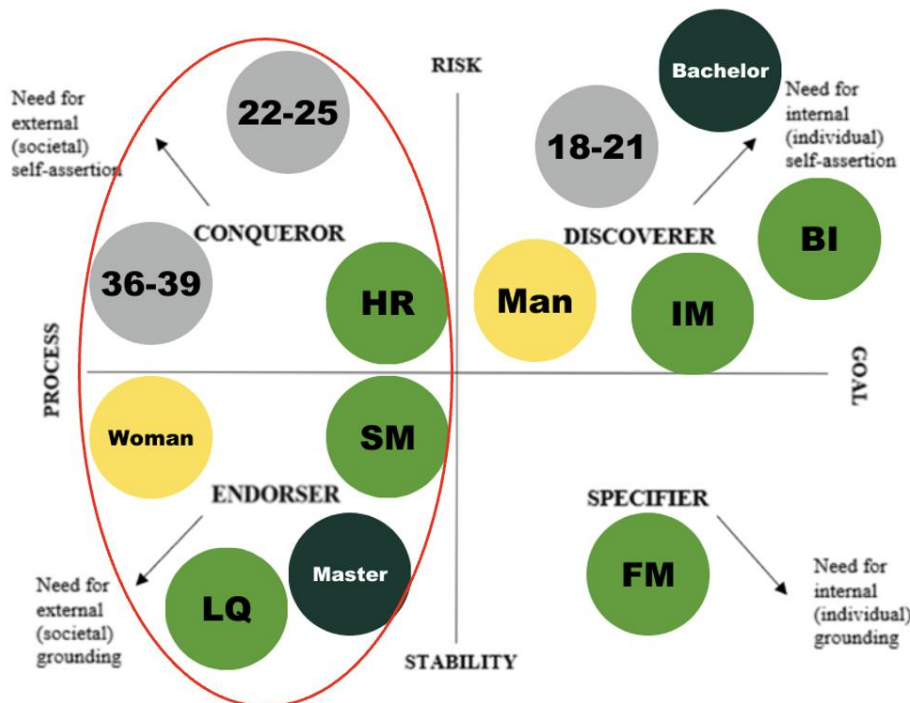


Figure 2. People preferring task type "HOW" by various criteria
Source: the authors

4. 2 Evaluation process

The managers of Škoda Auto a.s. and Škoda Auto University o.p.s. subsequently evaluated the completed tasks. Facilitated discussion brings many benefits for academic research and practical applications, mainly due to its ability to generate more profound understanding and consensus among stakeholders. It allows participants to share their experiences, perspectives, and suggestions in a structured but open dialogue, leading to the discovery of new perspectives and solutions. In the context of our research, facilitated discussions with senior leaders enabled the identification of practical barriers and opportunities for more effective use of AI in work teams through an interactive process highlighting the importance of collaboration and shared understanding. This approach encourages innovation and adaptation to change, strengthens organisational culture, and increases employee engagement in decision-making and implementation of new technologies.

4. 3 The experiment

Finally, based on the findings from the comparison of human work and AI-generated outputs, an experiment was conducted to explore the synergy between human creativity and the analytical capabilities of the AI system; after a detailed analysis of the results from the previous phases, the most successful focus group participant was selected and tasked to use the AI system that was deemed most effective based on prior evaluations - namely ChatGPT - to complete the same task. This approach aimed to combine unique human skills with AI's computational efficiency and objectivity to achieve the optimal solution to the task.

4. 4 Characteristics of the task

Building on the findings from the previous research investigation (Pechová, Volfová, Jírová, 2024), a process-based task was designed, the structure and parameters of which were carefully designed to reflect all the key aspects identified in the study. The task was formulated with an emphasis on explicit definition and the provision of complete and specific information to enable its precise and efficient execution. The task specification included the creation of an invitation to a three-day team meeting to be held at the Clarion Hotel Špindlerův Mlýn on 23-25 March 2024. The brief emphasised that the task was highly prioritised and not considered confidential. The main objective of the assignment was to ensure that all employees were informed in a timely and adequate way about the planned meeting, the attendance of which was defined as mandatory for all team members.

"Dear "completed name of respondent", please create an invitation to a three-day team meeting of the working team in the first half of 2024. The team meeting will be held at the Clarion Hotel Spindleruv Mlyn. The date is 23-25 March 2024. The task is not confidential and has urgent priority. The purpose of your assignment is to inform your colleagues in time about the planned meeting, which is mandatory for all employees. Thank you for your handling, and I am counting on you. Jana

In addition to a detailed description of the task, a task guide was also provided, containing instructions and recommendations on how to complete the task effectively. This guide was developed to facilitate completing the task while supporting the participants' development and application of key skills. Within this guidance, mechanisms were also put in place to provide support to participants who requested it, ensuring that the approach was flexible and adaptable to the individual needs and preferences of participants.

5. Results of research investigations

5. 1 Evaluating human tasks

The "winning" invitation was selected using multi-criteria decision-making and pairwise comparisons at a WS with managers of Škoda Auto College Inc. and Škoda Auto Inc. on 23 February 2024. The managers identified in chap. 4, were shown all fifty completed tasks and a decision was made on the task that scored best according to the defined criteria. If there was a score match, the pairwise comparison method was chosen to make the final decision.

Suppose multiple evaluation criteria and problem-solving options are specified, and the weights of each criterion can be determined according to their importance. In that case, the multi-criteria decision-making method can be used to decide. The multi-criteria decision-making method allows the options to be ranked from best to worst in order of preference. It must be taken into account that there is rarely one solution option that is the most advantageous according to all the chosen criteria and that the criteria may be contradictory. This method is suitable for decision-making situations arising under conditions of risk and uncertainty and for decision-making situations that are exclusively rational. Decision matrices and decision trees are also suitable for rational decision situations determined by risk or uncertainty. A decision matrix is essentially a table where the different options for solving a situation form its rows, and the chosen criteria for evaluating the options form its columns. The aim is to determine the most favourable decision option by calculating the criteria and their importance determined through weights. Although the use of decision matrices is based on rational reasoning, the determination of variants and weights can only be subjective, and this then applies to the nature of the optimal variant (Štrach et al., 2023).

Fig. 3 shows the completed winning task of the "HOW" type, which was implemented by the people in the focus group. It was then compared with other tasks performed by AI systems presented in Sect. 4.2.



Figure 3. Task carried out by people within the focus group
Source: the authors

The quality of the information was at the same level in the evaluated tasks. Given the information processing guidelines developed and the respondents' responsibilities, there were almost no differences between the evaluated outputs.

The speed of the completed task ranged from 12-36 minutes. Figure 3 presents the task completed the fastest; however, it should be taken into account that the focus group participants worked in conditions that eliminated communication noise, e.g. physical noise, psychological noise, etc.

Within the criterion of comprehensiveness of information, the highest differences in the scores of individual tasks were recorded. The top positions were occupied by the realized tasks, where email links were automatically inserted in the invitation to confirm participation, the exact address of the venue or even information processed with a QR code. At the same time, the evaluators preferred the processed tasks in the Czech language. They justified their decision because the development event will be held in Czech, so there is no need for English or any other language on the invitation.

The graphical form of the task emerged as the criterion with the lowest weight of importance. Although there were high score differences in this criterion, and indeed, some invitations had very creative and pleasing graphic design, this was the least important to the evaluators. For example, the winning invitation did not meet this criterion at all.

In the last criterion above, managers were reluctant to provide additional support to accomplish the task. They assume that if the task is given as a "HOW" type, there is a guide for completing it, and the task is relatively routine; no additional support is needed. The invitation visualized above was created without any extra support from the assignor.

5. 2 Evaluating tasks processed by AI

Section 5.2 presents the results of another qualitative investigation. AI systems such as Chat GPT, Bing AI, Alphabet's Bard (now Gemini), Midjourney or DALL-E were given an identical task to those in the focus group. The exact wording of the task is given in chap. 4.4. The task was given in Czech. At the same time, the task was

again selected as the winning task by the managers at the WS on 23.2.2024, according to the criteria listed below. Fig. 4 shows the completed winning task of type "HOW", which was implemented by the GPT system.

Dear colleagues,
I would like to invite you all to our upcoming three-day team meeting scheduled for March 23-25, 2024. This meeting will be held in the beautiful surroundings of the Clarion Hotel Špindlerův Mlýn, which will provide us with an ideal environment for our joint work, teambuilding, and relaxation.

Meeting agenda: over the course of three days, we will focus on several key topics and projects that are essential to our society. We will discuss achievements, set new goals, and look for the best ways to face the challenges ahead of us together. We will also have workshops, team building activities and plenty of opportunities for informal networking.

Attendance: I sincerely urge you all to book this date in your calendars as attendance at this meeting is mandatory for all employees. Your attendance and active participation are crucial to the success of our meeting.

Logistics: all necessary information regarding accommodation, agenda and transport will be provided to you in advance of the meeting. For any questions or specific requirements, please do not hesitate to contact the organizing team.

Registration: please confirm your attendance by 15 February 2024 via email to [organizing team email]. This will allow us to better plan and arrange everything necessary for a comfortable meeting.

I look forward to meeting you all in person and spending productive time together in the beautiful surroundings of Špindlerův Mlýn. Thank you for your cooperation and commitment to the success of our team.

Sincerely,
[Your name and position]

Figure 4. Task implemented by the GPT system (translated)

Source: the authors

The task implemented by the GPT system was best evaluated within these defined criteria:

- Quality of information (e.g. accuracy)
- Speed of task completion
- Comprehensiveness of information
- Graphic design
- Level of support from the contracting authority

The quality of the information varied at different levels in the individual systems, and the least successful were the DALL-E and Midjourney systems, which did not understand the task given in Czech. Bing AI inaccurately stated the location of the development action. The highest scoring was Chat GPT, which accurately stated the date and location of the development action. However, none of the outputs examined were rated with the maximum number of points.

The speed of the completed task ranged between 15 and 40 seconds, and there were almost no differences between the outputs.

Within the criterion of comprehensiveness of information, the highest differences in the scores of individual tasks were recorded. According to the evaluators, Chat GPT structured the information best, formulated it in a motivating way and was even the only system examined that required confirmation of participation by a specific date. It also listed several particular activities that could be implemented during the team meeting and highly praised the environment in which the event would occur. The Bing AI system was rated the lowest in relation to the defined criterion.

None of the above-mentioned AI systems met the criterion of graphical form of outputs. The Anaphabet Bart system stated that it cannot create images. Chat GPT graphically produced fascinating thematic images, but the information embedded in them regarding the date and location of the development event needed to be more meaningful. Bing AI, DALL-E and Midjourney submitted images the evaluators felt were inappropriate for a teambuilding event. Figure 5 presents the output of the completed tasks using the Bing AI system.



Figure 5. Completed task using Bing AI
Source: the authors

In the last criterion mentioned above, the evaluators' reluctance to specify the task further and better was evident, and none of the examined outputs met the defined criterion. Each of the systems mentioned above needs additional AI user competencies and has its specifics for task assignment.

5.3 Comparison of results

To synthesize the findings, a comparison was made between tasks processed by human participants and AI systems such as ChatGPT, Bing AI, Alphabet's Bard (now Gemini), Midjourney and DALL-E, to evaluate their performance according to the following criteria: quality of information, speed of task completion, comprehensiveness of information, graphical form and level of support from the tasker. This structured analysis offers more profound insight into the capabilities and limitations of both human labour and AI technologies in processing and completing specific tasks.

Information quality (especially accuracy): both human teams and AI systems, especially ChatGPT, have achieved high levels of information quality and accuracy. However, the human teams tended to add more contextual knowledge and nuance to the tasks, reflecting a deeper understanding of the topic. Conversely, ChatGPT and other AI systems excelled in quickly processing and providing accurate information, but sometimes without deeper contextual understanding.

Speed of task completion: In this category, AI systems significantly outperformed human teams, completing tasks in seconds because of their ability to process information instantaneously. Human teams took longer to complete the same task, reflecting the time required for analysis, creative processing, and quality control.

The comprehensiveness of information: human teams typically provided more complete and detailed information that reflected a comprehensive understanding of the task and its objectives. While AI, particularly ChatGPT, could provide extensive information, it sometimes lacked depth and alignment with the specific needs of the task. Human teams were also more responsive to the need for adaptation and providing complex answers.

Graphic design: in the area of graphic presentation, people's work was considered to be of higher quality because it could better reflect specific design and aesthetic requirements. AI systems, such as DALL-E and Midjourney, had limitations in producing graphically appealing outputs that also met the assignment's specific requirements.

Level of Assignor Support: Human teams require and value feedback and support from the assignment assignor, allowing for iterative refinement of outcomes. AI systems are limited to the instructions given and thus can only easily adapt their outputs based on additional feedback if it is directly coded into their program.

This comparison shows that while AI systems can offer significant advantages in speed and efficiency for certain types of tasks, human teams still prevail in areas requiring deep understanding, creative processing, and aesthetic evaluation. Human interaction with the task also brings value in the form of adaptability and flexibility in response to unexpected demands or the need for change, something AI currently cannot fully emulate. Additionally, when dealing with complex tasks that require a multi-disciplinary approach and deeper contextual understanding, human teams can better integrate different information sources and perspectives, creating richer and more customized solutions. While AI can provide powerful support for data processing and automation of repetitive tasks, human skills of critical thinking, empathy, and creativity are key to solving more complex and less structured problems.

It is also important to emphasise in the context of assignor support that the success of any assignment depends not only on the performer's skills but also on the quality of communication and clarity of the assignment. While AI can work effectively with well-defined instructions, human teams can better navigate situations where the assignment is ambiguous or requires additional clarification.

Thus, the comparison suggests that the most effective approach to task performance in the modern work environment will likely lie in the synergy between human and AI capabilities. Integrating AI can maximise efficiency and accuracy while the human element remains essential for tasks requiring deeper understanding and creative processing, making achieving higher productivity and higher quality outputs possible.

Following identifying key insights into the synergy between human capabilities and the potential of AI, we proceeded to an experiment to practically test this synergy in action. The experiment consisted of assigning a task initially designed for focus group participants whose outcome was evaluated as the most successful but with the additional requirement of using artificial intelligence, specifically the ChatGPT system, to implement it. This approach aimed to combine the deep understanding and creative approach of humans with AI's computational efficiency and speed. As part of the experiment, the participant was provided with the top-rated AI system, ChatGPT, with instructions on using this tool to maximise the task brief, including generating the relevant image. Armed with a deep understanding of the task and the specific needs of the project, the participant was encouraged to provide the AI system with the most accurate and detailed instructions to ensure that the resulting work met all criteria.

5. 4 Task assignment process in human-AI collaboration

Communication between the human participant and ChatGPT 4.0 was an interactive dialogue, where the participant provided specific instructions and feedback on iteratively generated suggestions from ChatGPT. This process involved several steps, from initial input to final edits, leading to the creation of an optimal invitation.

Step 1: Task definition

Participant: "I need to create an invitation for a three-day team meeting to be held on 23-25 March 2024 at the Clarion Hotel in Spindleruv Mlyn. The invitation should be brief, informative and visually appealing. It should include the date of the meeting, the location, the main programme points and a contact to confirm attendance.

The brief is as follows:

Dear "completed name of respondent", please create an invitation to a three-day team meeting of the working team in the first half of 2024. The team meeting will be held at the Clarion Hotel Spindleruv Mlyn. The date is 23-25 March 2024. The task is not confidential and has urgent priority. The purpose of your assignment is to inform your colleagues about the planned meeting, which is mandatory for all employees, on time. Thank you for your handling, and I am counting on you. Jana

Step 2: First proposal from ChatGPT 4.0

ChatGPT: "I created a draft invitation. It contains all the required information and is accompanied by a basic graphic design. I would like to get your comments on the content and design."

Step 3: Feedback and adjustments

Participant: "The content looks good, but could you add more details about the meeting agenda and especially select the most important information so that even a less attentive reader can pick up the key information? Also, highlight the contact section to confirm attendance. I would also like the graphic design to correspond more with the theme of teamwork. Also, don't include any text in the visual; this will be added afterwards."

Step 4: Further suggestions and adjustments

ChatGPT: "Based on your feedback, I have modified the content and design of the invitation. I have added a more detailed program description and improved the graphic design. How do you like the new design?"

The human participant and the AI interacted with the content through further modifications, where minor modifications were always specified, especially according to the knowledge specified in the event program. Significant interaction was also noted in the creation of the visuals, where ten different versions were generated before the visual was appropriate to the task, e.g. in the form of a prompt: I need the mountains, teamwork and joy to be accentuated. The overall communication is less relevant to this article than the introduction of the process.

Step 5: Final approval

Participant: "The new design looks good already! The program is clearly described, and the graphic design fits our theme. This invitation now meets all our requirements."

The result of this experiment was exciting. Using instructions from a person who had already completed the task, ChatGPT could efficiently process the information and generate text that matched the required criteria and create a visually appealing visual to complement the task. The limitations of creating graphics with ChatGPT are well known, so an approach based on generating a visual of the event was chosen, with essential information added after the fact. The human participant provided context and direction to the AI system, while the AI brought speed, accuracy, and content generation capability, which together resulted in a solution that maximally met the requirements. This output demonstrates how human guidance of AI - by providing clear, structured, and context-rich instructions - can significantly enhance the quality and relevance of AI-generated outputs. Human-AI collaboration can enrich work processes and outputs, opening new possibilities for future applications of AI in practice. The experiment thus provides valuable insights for further research in this area and offers a new perspective on optimizing work processes using AI technologies.

Output generated in collaboration between a human worker and AI

Fig. 6 shows output generated in collaboration between a human worker and AI. This situation clearly shows that the key to the successful integration of AI into work processes is not only the technological development of the AI systems themselves but also the ability of people to interact with and manage these systems effectively. The symbiosis of human creativity, intuition, and adaptability, along with AI's speed, accuracy, and data capacity, is a powerful combination that can bring new levels of efficiency and innovation in many areas.

Invitation to the team meeting

Dear colleagues,

It is my pleasure to invite you to an important team meeting, which will take place in the beautiful surroundings of the Giant Mountains. This meeting is a key milestone for our team and represents an ideal opportunity to strengthen our collaboration.

Meeting Details:



- **Date:** 23-25 March 2024
- **Place:** Hotel Clarion, Spindleruv Mlyn
- **Participation:** mandatory for all team members

Program

- **Day One:** Opening with a welcome speech by our CEO, followed by workshops on innovation and strategy.
- **Day 2:** Team-building activities in nature and evening discussion circles around the fireplace.
- **Day 3:** Presentation of team projects, evaluation of the meeting and planning of next steps.

Important information: please confirm your participation by 15 February 2024 by replying to this email: [email of the organiser]. In case of questions or specific requirements, please do not hesitate to contact the organizing team.

Detailed information regarding accommodation and transport will be sent to registered participants.

We look forward to spending productive and memorable times together that will not only strengthen our team spirit, but also find new ways to face challenges and achieve our goals.

We look forward to your participation and contribution to the success of our meeting.

Sincerely,

[Surname]
[Position]

Figure 6. Output generated in collaboration between a human worker and AI
Source: the authors

This approach also highlights the importance of developing digital skills and understanding AI among the workforce, which are key competencies for the 21st-century workforce.

Conclusions

This paper investigates the effectiveness of task performance between humans and AI systems, focusing on "HOW" tasks. Through a comprehensive research investigation, we examined how human teams and AI systems cope with the challenges of performing specifically defined tasks and what factors contribute to their effectiveness.

The main objective of our study was to compare the effectiveness of "HOW" tasks between human teams and AI, with sub-objectives aimed at identifying key factors influencing this effectiveness. The results of our investigation clearly show that AI systems, especially ChatGPT 4.0, can outperform human teams in certain aspects, such as speed and accuracy of information. However, when it comes to depth of understanding, creativity, and adaptability, human teams still hold their position firmly as an indispensable element of an effective work process. The sub-objectives of this study have been successfully met through a comprehensive analysis and comparison of the performance of human teams and artificial intelligence systems in performing "HOW" tasks. The first sub-objective was to identify the key factors influencing human teams' task

performance effectiveness. Using qualitative and quantitative research methods, we discovered and documented how the scope of the task, clarity of instructions, and the ability of teams to adapt to changing demands affect task performance. The second sub-objective was to assess how AI systems perform on tasks compared to humans, which we did by comparatively analyzing the performance of the two groups based on predetermined criteria. The results showed specific strengths and limitations of AI in the context of task performance, particularly in processing speed, information accuracy and content consistency, but also highlighted the need for human intervention for creative solutions and contextual adaptability. Thus, this study provides valuable insights into the synergy between human capabilities and AI, suggesting the optimal use of their combination to enhance the efficiency of work processes.

One of the key findings of our study is that synergy between human capabilities and AI can lead to optimized efficiency and quality of task performance. An experiment in which a human participant used an AI system to accomplish a task demonstrates the potential of this synergistic collaboration. With the combination of human understanding, creativity, and intuitive guidance from the AI system, a solution exceeded expectations in all evaluated criteria.

This paper thus makes an essential contribution to understanding the dynamics of task efficiency in the AI era. It confirms that while AI systems are a powerful tool for streamlining and automating processes, the human element remains essential to ensure outputs' depth, quality, and adaptability. For organisations, the integration of AI should be done with a view to its complementary role to human capabilities to create a working environment where the potential of both is maximised.

Our findings thus open the way for further research and discussion on combining human skills and AI to achieve the highest possible efficiency and innovation in different areas of working life. They also highlight the importance of developing digital literacy and AI skills amongst the workforce to enable them to interact effectively with these systems and maximise their potential.

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ARTICLES FOR FACULTY MEMBERS

CLIMATE CHANGE AND SEA TURTLE NESTING

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Abstract. With the rapid advent of the new information and communication technologies, including fast development of the Artificial Intelligence, the digitalization process could be considered as a basic key element of the transition process, securing the sustainability of an organization. This is also relevant for the Higher Education Institutions that have very significant and at the same time responsible role to prepare well the next generation for the challenges of the labor market. Therefore, the effectiveness of the digitalization at the universities is critical for two major aspects: to secure proper education based on the cutting-edge technologies and to provide good quality of all accompanying administrative services. This article presents the potential indicators determining the effective level of digitalization in higher education institutions. These indicators are developed based on the empirical study among 360 universities students in Master and Bachelor degrees in leading Bulgarian universities. Our findings indicate that students generally positively evaluate the efforts of universities to digitize the educational process. At the same time, some aspects of the educational process - such as the assessment in a digital environment, or the provision of administrative services - such as the application for dorm accommodation, which should be improved, are outlined. However, the need to make constant efforts to protect personal data and provide quality educational digital content is considered. We propose 9 complex indicators for assessment the effectiveness of digitalization in university.

Keywords: digitalization; higher education institutions; digital educational resources; digital education

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1. Introduction

One of the most important objectives in front of every Higher Education Institution (HEI) is to provide quality education in order to prepare well next talented young people for the challenges of the labor market. At the same time, this educational service must be consistent on the one hand with the requirements of the business, and on the other - with the educational standards and the maintenance of high-quality education. In the era of information and communication technologies (ICT) and the extremely strong development of Artificial Intelligence (AI), it is impossible to provide quality education if a high level of digitization is not sufficiently ensured. The process of digitalization in HEIs has to be considered as multifactorial and complex and respectively the determination of indicators for its effectiveness is the main object of the current study.

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From the very first universities to our days, it can be said that they are not just institutions of education where some people try to transfer their knowledge and skills to other people. Universities create an entire environment, worldview, form critical thinking, encourage their students to discover and develop their potential and opportunities. In this sense, every single university can be seen precisely as an opportunity for young people - to prove themselves that they know, that they can, and that they are ready for the challenges of tomorrow – equipped with knowledge skills and abilities required by business organizations.

For any serious university nowadays, digitization and the digitization process are a key to guaranteeing a quality education recognized by academy community, young people and businesses. Of course, digitization can be found in everything - from a quality university website that is easy to navigate, search for information and provide access to any educational platforms, through online application, inclusion in certain courses and access to digital educational resources to, for example, submitting documents for student accommodation.

The key understanding of digitalization, shared by the authors of the current article, should be sought not in the exact reproduction of the traditional process in a digital environment and their implementation with digital tools, which simply copy the currently existing traditional process, but in the way to improve its efficiency - less time, less resources, more options, etc. Therefore, just having a digitized process is not enough prerequisite to ensure efficiency of organization - it is necessary to consider these processes in their complexity and systems and in the opportunities for improvement. The present article defines namely the indicators for securing effectiveness of the digitalization in HEIs. The proposed indicators are identified on the base of the empirical survey among 360 students in leading Bulgarian universities.

2. Theoretical background

Digitization, digital services and their applicability in all aspects of our modern life are in the top focus of the scientific discussion and interest for the last few years. This interest is logical and easily explicable due to the fact that digitization and the provision of digital services can bring the development of any organization to a completely new level. The business organizations are the most adaptable and flexible to the rapidly changing demands of the external environment, but the public authorities and organizations from other social systems have also changed following the digital trends, albeit at a slower pace.

The interaction between universities and industries in terms of digital transformation and digitization is one of the most vivid scientific discussions at the moment. For some researchers this collaboration is considered as a driver needed both for industries and universities for achieving sustainable transition to the new economic development. Evans, Miklosik and Du (2023) consider that the advantages of the partnership between businesses and universities encompass gaining valuable resources, validating work, facilitating learning and teaching opportunities, financial gains, enhancing reputation, and advancing career prospects. Albats, Alexander and Cunningham claim that intermediaries in relations universities and industries are shifting from physical to virtual and digital formats. Some interesting researches in the relation line between industry and universities but in more general context are explored by different scholars: Meissner et al. (2022) focus on the role of the labs, created as a result of partnership between industry and universities; Roncancio-Marin et al. (2022) consider the social impact of this collaboration; Alpkan and Gemici (2023) examine the synergy effect from this partnership for the product innovations; Zhang et al. (2021) explore the role of this collaboration for the creation of new technology companies. Silva et al. (2021) made comprehensive research to identify the milestones of successful collaboration and propose a model for sustainable partnership.

Based on a comprehensive research and data analysis, Ma and Li (2022) revealed an interesting correlation between the level of digitalization and from the other side – relations between enterprises and universities. They concluded that the digitization process facilitates the transfer of knowledge from universities to businesses and identified indicators to assess digitalization in different dimensions. The scholars selected indicators covering 5 different aspects of digitalization which are: digital facilities, digital carriers, digital communications, digital applications, and digital finance (ibid).

The possibilities of digital learning, as well as its limitations, is also one of the main topics when it comes to digitization in education system, especially after COVID-19 pandemic. Liu et al. (2023) made an interesting research on the digital capability of university students, and concluded that for students, attributes such as innovative capability, the application of big data, and employability skills are crucial factors connecting digital capability with sustainable behavior. Similar research was made by Reinhold et al. (2021) whose major conclusion is that positive attitude of students towards e-learning is the key element for success in digital education. Different aspects of e-learning coming from different countries around the world and its impact on both on students and teaching staff is explored by Zaharia et al. (2022), Weerathna et al. (2023), Liu (2023), Stoykov and Petrova (2023); Angelova (2020), Salahshouri et al. (2022), Manjeese (2022), Al-Okaily et al. (2020) etc.

Tautz, Sprenger and Schwaninger (2021) focus their scientific interest on the digital tools that could improve digital learning such as Virtual reality, question tools, classroom response system, lecture recording etc., in order to understand their impact for the active learning of students. Their main finding is that the students are willing to use digital tools in learning and consider this as a form of diversity (something new), which enrich the lecture (ibid).

Liu, Lee and Huang (2023) explore the possibility how could be boosting creative confidence, motivation for learning, and the collaborative creative performance of university students in design thinking through the utilization of a digital visual collaborative environment. Elnadi and Gheith (2023) on the other side pay attention on the role of individual characteristics of students for their digital entrepreneurial skills and intention to do digital business. They found out that digital competence as well as passion and curiosity are key factors for digital business intention. In this line comes the research of Demsash, Emanu and Walle (2023) who explores the digital technology and its level of exploration from university students. Scholars made empirical research among university students for their digital skills and usage of technologies and outlined several factors for good level of digital exploration such as: previous computer experience, favorable attitudes, good internet access (ibid). Almost the same subject is explored by Alferaih (2022), who also study the intentions of the university students for doing digital entrepreneurship. Scholar admit that factors such as attitude, subjective norm, perceived feasibility, perceived desirability, propensity to act, digital entrepreneurial education, and innovativeness play a substantial role in influencing entrepreneurial intentions. Additionally, perceived behavioral control and self-efficacy significantly impact actual entrepreneurial behavior (ibid).

Chan, Krishnamurthy and Sadreddin (2022) investigate the ways in which digital tools, particularly technologies encompassing social, mobile, analytics, and cloud (SMAC), enable both internal and external interactions within university incubators and various participants in the entrepreneurial innovation ecosystem.

Some of researchers explore the specific digital services provided by universities. For instance, Litoussi et al. (2022) consider the practice of universities for providing digital certifications (such as official academic transcript, registration certificate, diploma) and propose a model for decentralization of digital certification using blockchain technology. Ahmad and Rafiq (2022) assess the level of digitalization readiness of the university libraries and secure the digital preservation of the available literature. The results of their research reveal that libraries demonstrated a high level of readiness only in terms of having sufficient funds for acquiring technological infrastructure, while lack of adequate policy and procedure for digital preservation, training opportunities and skilled human resources are pointed out as insufficient (ibid).

Zeqiri et al (2023) admit that students' satisfaction nowadays is a complex magnitude, but on the other side, the quality e-services provided by university, including trough web-site and intranet pages of the universities are one of the factors that are directly connected and impact the students' satisfaction.

Guerrero, Heaton and Urbano (2021) explore the real possibility of new level of development of universities through the Massive Open Online Courses (MOOCs) which they consider as a chance for university to regain competitive advantage in digital era and digital economy. The main benefit that MOOCs provided, identified by Ogunyemi, Quaicoe and Bauters (2022) is the huge potential for massive audience which is geographically dispersed and absolutely heterogenous in its basic characteristics. On the other side, Dang, Khanra and Kagzi

(2022) study the limitation in front of the MOOCs and reveal the following major groups – usage barriers, value barriers (including poor content quality etc.), tradition barriers and image barriers (including accent of the lecturer etc.). Interesting researches for different aspects of MOOCs are developed by Wong, Baars, de Koning and Paas (2021), Aparicio et al. (2019), Weinhardt and Sitzmann (2019), Janelli and Lipnevich (2021) and others.

On the other hand, McLean, Maalsen and Lake (2022) pay attention to something very important – how university can secure the digital sustainability in long terms period. They conducted a study at the University of Sydney and one of the conclusions they reached was that digital sustainability is not yet at the center of strategic sustainability planning efforts.

In summary, the process of digitization in universities represents a transformative journey that extends beyond mere technological integration. Embracing digitization opens avenues for enhanced learning experiences, improved collaboration, and increased access to information. The benefits extend to both students and educators, fostering a dynamic and interactive educational environment. Additionally, digitization enables universities to streamline administrative processes, optimize resource utilization, and stay abreast of evolving educational trends.

3. Methodology of the research

Our main objective of the current study is to identify workable indicators for determining the effective level of digitalization in the higher education institutions, considering the two major aspects in any university: the core educational process itself (with all levels and forms) and all accompanied services – including different administrative services and securing access digital record and online educational platforms and resources. This study is a part of the entire scientific project title, financed by Bulgarian Science Fund.

In order to achieve the above-described objective, we implemented the followed methodological steps, presented in Table 1.

Table 1. Methodology, used for the achieving the main objective of the research

METHODOLOGY OF THE RESEARCH	
1.	Discussion and determination of the most thorough and effective way to achieve the research objective
2.	Preparation of questions for semi-structured interviews and task allocation between authors
3.	Identification of the major target groups and their concrete representatives for the interviews
4.	Collecting initial information through semi-structured interviews
5.	Developing an initial set of questions to be used in the questionnaire
6.	Pilot testing the quality of questions and their order in the questionnaire
7.	Finetuning of the questionnaire according to the result of the pilot test
8.	Distribution the questionnaire
9.	Conducting the empirical study – collect responses
10.	Analysis of the collected information
11.	Identification of workable indicators for the assessment of the effective level of digitalization in HEIs

Our first step was to discuss and agree on the most appropriate and effective approach for the overall methodology of the research. In order to obtain initial information about the process of digitalization in university, we decided to conduct several semi-structured interviews (21 in total) with different representatives of our major target groups - academic staff, management body, administration and students. Although different groups can be presented in more comprehensively, for the purposes of our study we have identified the above four groups, with their main roles in the digitization process of a university shown in Table 2.

Table 2. Major target groups, their role and characteristics in the digitalization process of a university

Main target groups	Role	Characteristics
Management Body	Decision makers	They lead the entire process of digitizing the university, including making decisions about the different systems to be used, ways to ensure connectivity and security. They are also the people who make decisions about the overall strategic development of digitization in the university.
Academic Staff	Users with different level for access and activities	Regarding the different platforms used for distance learning, the academic staff should have more rights than the average user - including managing different groups, being able to create groups, assign tasks and monitor deadlines for their completion, etc. At the same time, in purely administrative aspect, academic staff has access to the systems for entering and signing grades - i.e. to student files etc.
Administration	Service and maintenance	Administration representatives at each university are responsible for maintaining systems and providing administrative services, from different documents to applying for scholarships. At the same time, the administration works on a daily level with these systems, enters information and their opinion is very important in relation to the overall digitalization approach of the university.
Students	Users	The most important target group, as universities are devoted to create communities of active, intelligent young people. In the sense of digitalization, they are the main users of university systems, especially in terms of access to platforms with educational materials and platforms on which distance online learning takes place. At the same time, however, students are also users of all accompanying administrative services, provided by universities. All this means that the final evaluation of the effectiveness of the level of digitization should be done precisely by this target group, since they are also the final beneficiaries.

The information collected as a result of these interviews we considered as very important for proper understanding of the overall digitalization of one university and not only the point of view of some of the stakeholders. However, even at this early stage of the research, differences in the focus of our target groups emerged. For example, for the representatives of the management structures, the emphasis was placed on ensuring the security of data and personal information of students and staff, for the representatives of the administration themselves, the most important thing was the easy maintenance and service of the various systems, as well as their connectivity, so as not to be required repeatedly or several times entering the same information into different systems. At the same time, academic staff emphasizes the preservation of the quality of the educational process and the need to keep the attention of students in a digital environment, including by using various digital new tools for this purpose. In turn, for students, one of the most important advantages is the possibility of easy access to educational resources and the possibility of a facilitated / distance educational process.

Based on the information, collected and analyzed from the semi-structured interviews, we developed an initial set of questions to be used in the questionnaire of our main research. Given the depth of the research, the initial version of the questionnaire was pilot-tested among students (as focus group), who were asked to say whether they understood the questions, whether there were questions with pre-formulated answers that did not fully exhaust the possible range of answers, whether they thought the questions themselves were correctly asked, lack of Ambiguity, etc. In general, the questions were relatively well developed, but it was necessary to reformulate three questions in order to achieve greater clarity.

After finetuning of the questionnaire, we distributed the information for survey among students in different universities. As a result of our efforts, we received 360 answers from university students both in Bachelor and Master degree.

4. Survey Results and Discussion

First section of the questionnaire collects information for the students’ profile (Table 3). The profile of our responders indicates serious predominance or representatives coming from the public university (91,1%), while the responders of the private universities remain modest (8,9%). This situation is easily explicable considering the fact that there are 52 universities in Bulgaria in total and the majority of them are public. According to data from the National Statistical Institute, approximately 12% of the university students in Bulgaria are in private universities. On the other hand, the administrative fee of the private universities could be considered as some kind of barrier in front of all young people who desired to study. Therefore, the number of students in private universities is in general smaller than the number of students in public universities, which fact is visible in our collected data.

Table 3. Combined data for the responders’ profile (in %)

Combined data for responders profile		
Status of the university	Public	Private
	91,1	8,9
Form of Education	Regular	Distance Learning
	91,4	8,6
Type of Educational Degree	Bachelor	Master
	95,6	4,4

In terms of form of education, the majority of our responders are in regular form (91,4%) and only 8,6% are students in Distance Learning form. This result does not really represent the correct proportion between students in the different forms of education. It is clear that our questionnaire was taken more seriously and more responsibly by the students in a regular form of education, while it did not arouse any interest at all in terms of students in distance learning. This can also be explained by the fact that distance learning students usually choose this because they work and study at the same time, which also explains their less commitment to a voluntary university study.

The vast majority of respondents are studying at a bachelor's degree, which is also understandable considering that a bachelor's degree is four years long, while a master's degree is between 1 and 2 years.

The second part of the questionnaire contains the questions on the assessment of the different aspect of digitalization in university, starting with those concerning education process. The next two questions are focused on the assessment of the learning process in digital environment. On the question “Did you like that the study was flexible – you could study from different places and at different times?” the accumulated results show that a large part of the responders rated positively the flexibility of the digital learning. A convincing 70,3% of responders declare their positive attitude to the flexibility which is one of the leading strengths of the digital learning process, versus only 25% whose assessment is negative. This question collects also almost 5% of hesitant students, who find some aspects of digital learning as positive and some – as negative ones (Fig. 1).

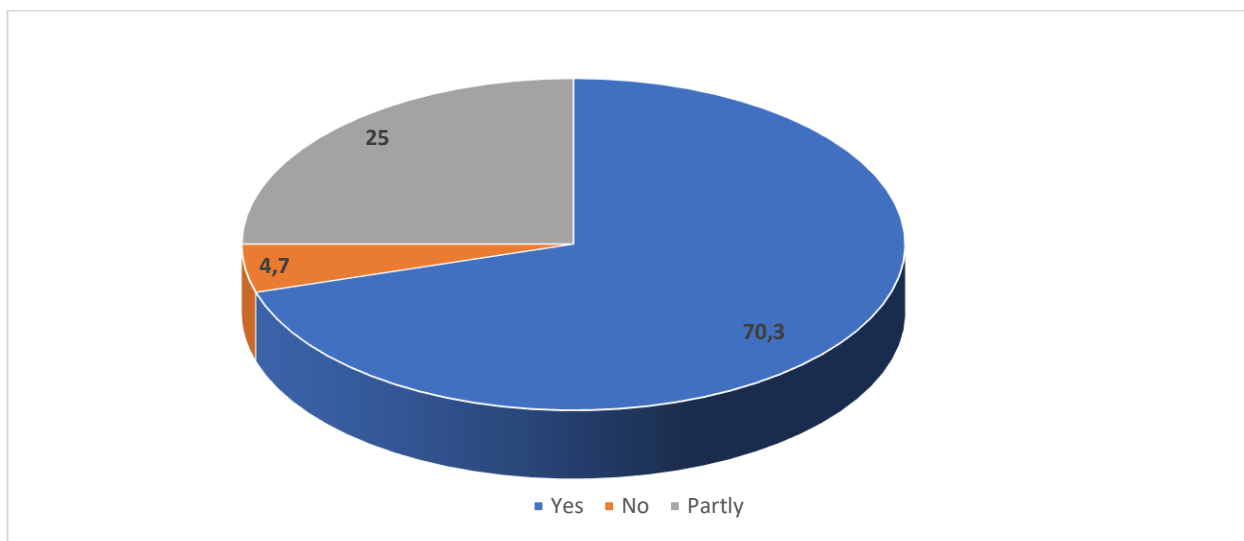


Fig. 1. Assessment the flexibility of digital learning, in %

“Did the new type of learning lead to higher personalization (to have emphasis / attention on the needs and problems of each individual learner)“ is the following question from the questionnaire. Here there is no such predominant preferred answer as was the previous question. However, 43,6% from responders admit that this type of learning meets individual needs of student and other 33,6% claim that these needs were met only sometimes. Here the share of responders with direct negative assessment is 22,8% which fact is indicative of the level of satisfaction or lack of satisfaction with regard to personalization achieved in digital learning (Fig. 2).

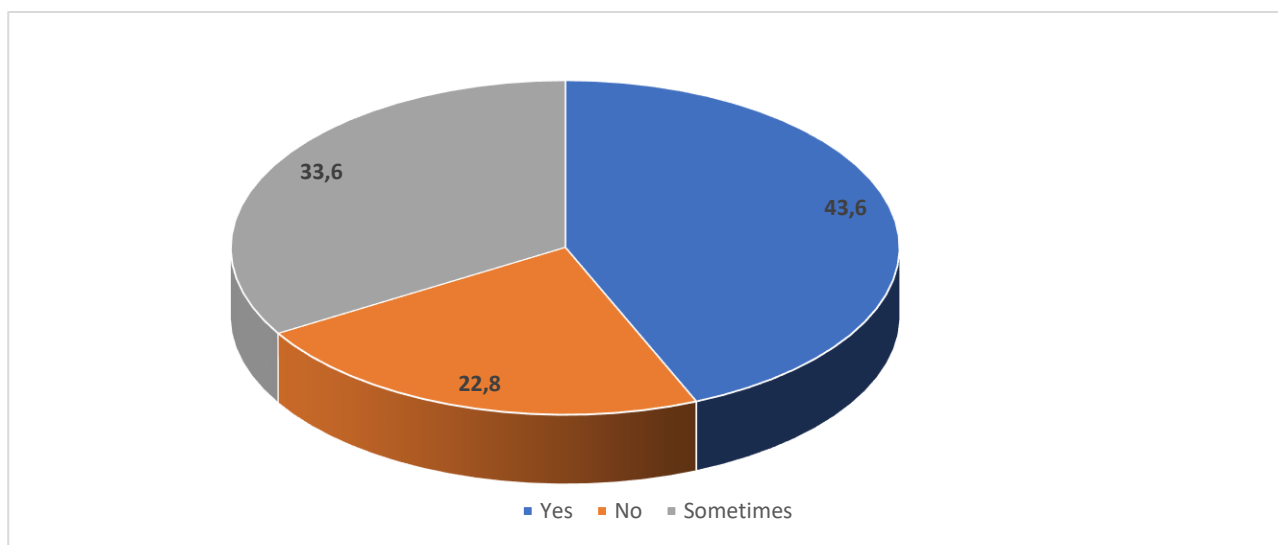


Fig. 2. Flexibility assessment of digital learning, in %

The next question “Was remote assessment good and effective?” presents an interesting distribution of answers (Fig. 3). Here the major part of responders claims positive assessment.

The completely opposite opinion is shared by 12,2 % of the respondents, who strongly disagree that remote assessment is good and effective. Here we have two other answers, the first of which (preferred for 11,1% of the responders) contains negative assessment for the start of the period, but at the same time – recognition that the assessment was improved during the time. However, 18,9% claimed to be rather positive about the current state of assessment now, but at the same time they admitted that they expect further improvement and development.

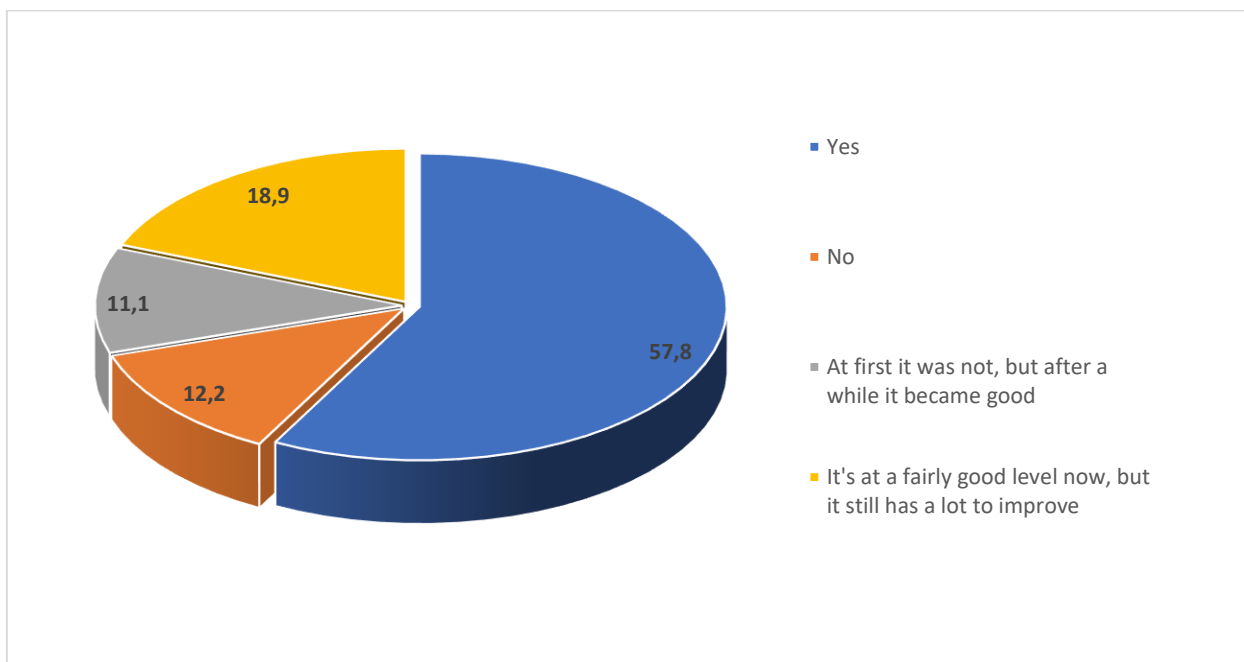


Fig.3. Evaluation on the remote assessment effectiveness, in %

The next question “What is the degree of digitization of the process of application and admission of students at the university” collects information for the overall process and for specific typical services conducted for this purpose: Document application; Acceptance of application documents; Admission to exam; Conducting competition exam; Admission of students based on their grades; Enrollment of newly admitted students (Fig. 4).

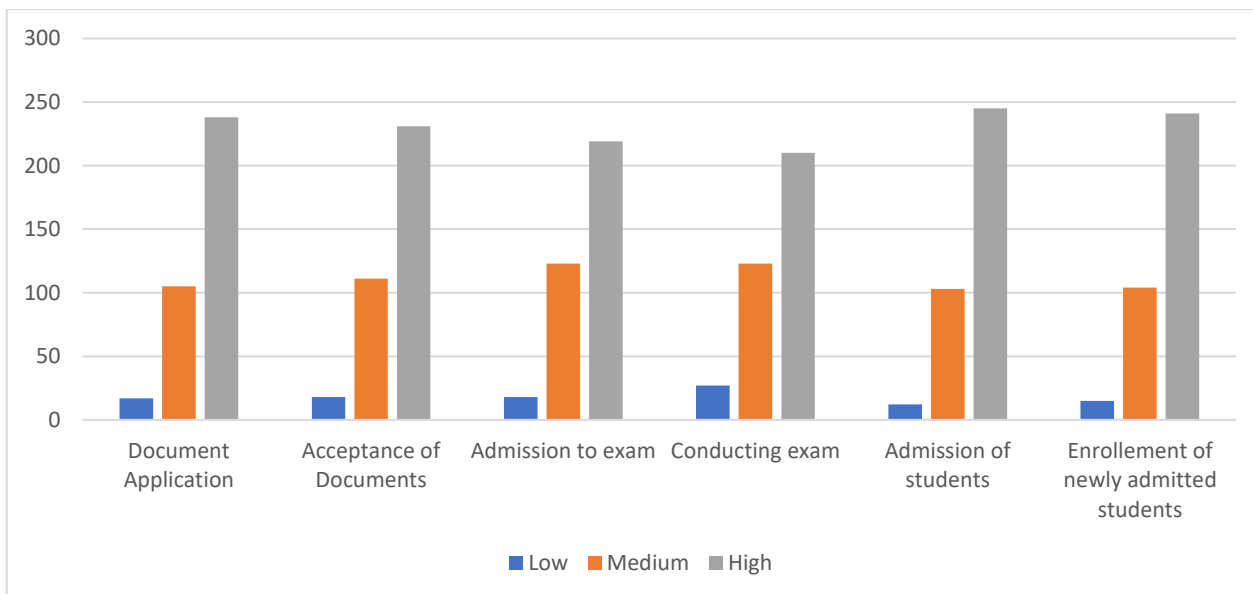


Fig.4. Assessment of the application and admission process of students at the university

As it can be seen on the figure above, the students predominant assess the level of digitalization of the process for application and admission in universities as high, with slight differences between different operations. According to their opinion, the admission of students based on their grades is the operation with highest level of digitalization, while the conducting of competition exam for admission is the operation with lowest level of digitalization (but this assessment still remains positive for the serious majority of responders).

The next question measures the level of digitalization of traditional administrative services for students. Here the results, especially compared to the results of the previous question, show that there are specific activities where the digitalization has to be drastically improved (Fig. 5).

Results indicate that service for Dorm Accommodation achieves the lowest assessment in terms of digitalization. This finding is clear evidence that students’ satisfaction on the digitalization level of the procedure for dorm accommodation remains insufficient and has to be further developed. At the same time this procedure is the only one from four, where the number of responders choosing assessment “medium” is highest than the number of responders with answer “high” for the level of digitalization. Apparently, the digitalization of the Study Schedule in the majority of the Bulgarian universities achieved the highest level of recognition from the students.

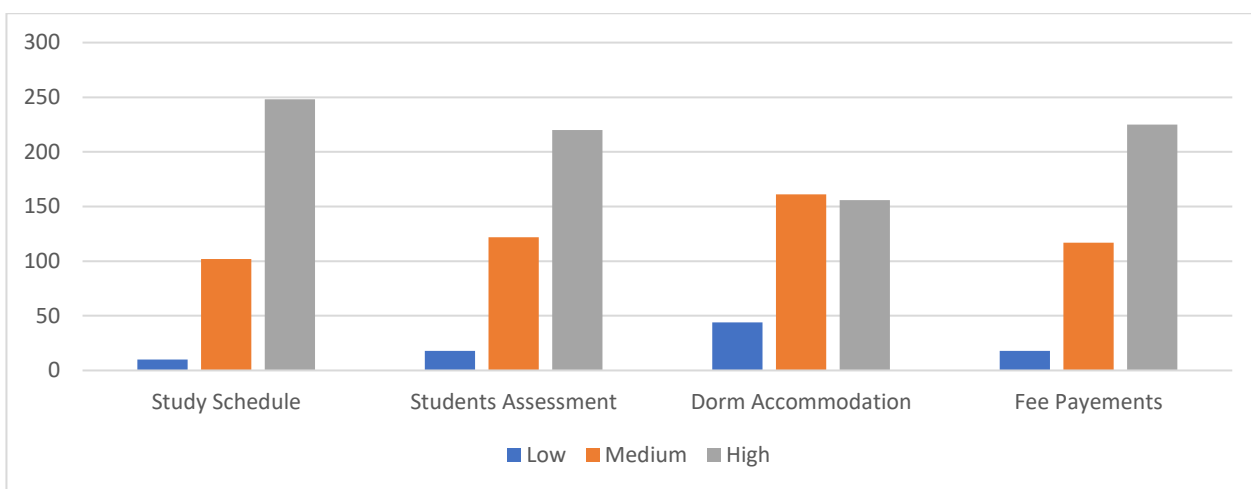


Fig. 5. Assessment of level of digitalization of traditional administrative services for students

Next question measures the level of digitalization in different forms of education – regular (full-time), part-time and distance learning. The results are explicable, considering the general idea behind these three forms of education. According to our responders, the digitalization in distance form of learning accumulates the highest assessment, while the digitalization in part-time learning remains the lowest (Fig. 6).

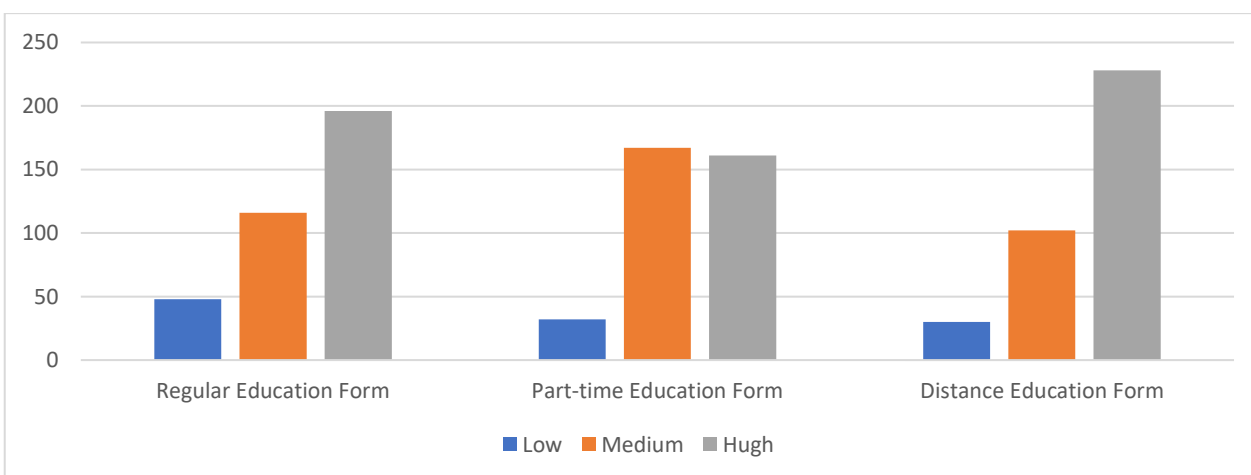


Fig.6. Assessment the level of digitalization in different forms of education

The results obtained for the next question reveal a clear picture for further improvements and development of the level of digitalization, developed so far by the universities. Interesting finding is the fact that students assess the level of digitalization during lectures higher than the level of digitalization during seminars. On the other hand, depending on the subject of the education itself, the lecture usually is more theoretically focused rather than the seminars, where it is expected to developed some skills and abilities more closely connected to the practice. In this regard sometimes, the digitalization could be difficult where the practical exercises are required (for engineering students, medicines students etc.). At the same time, the digitalization during the exams gains the highest level of assessment, comparing to the other activities. This is also logical, considering the fact that in almost all universities there are built test centers, used for this purpose (which support also the effort of the academic staff in assessment of students).

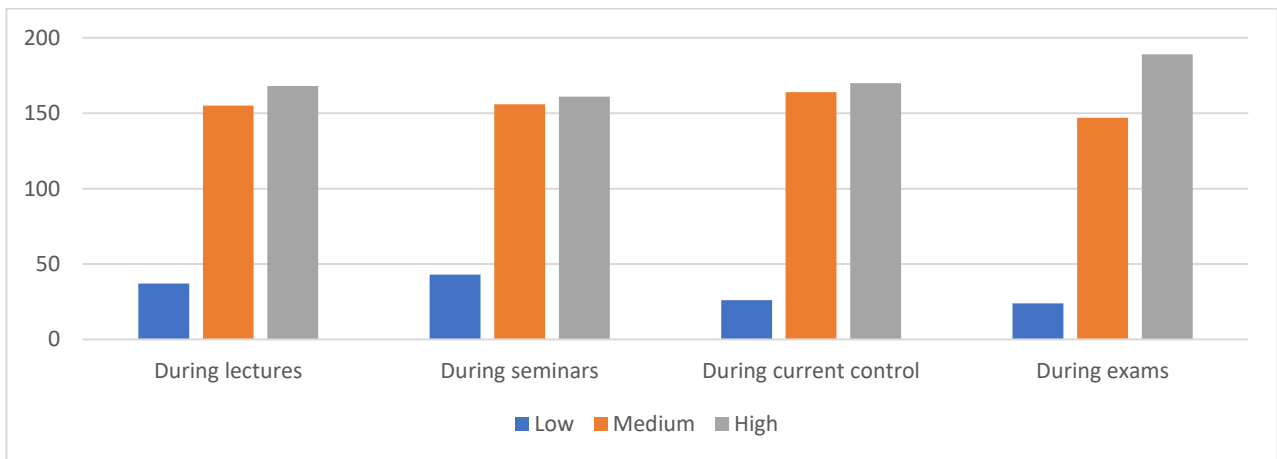


Fig. 7. Assessment the level of digitalization in different educational activities

One of the major problems when we explore the quality of educational process in digital environment is the content of educational material. The next two questions focus attention namely in this serious aspect of digitalization in HEIs. The question “Should educational institutions ensure/improve their online content and resources to be accessible to people with disabilities” shows the understanding of students on the accessibility of materials and resources for disable people (Fig. 8).

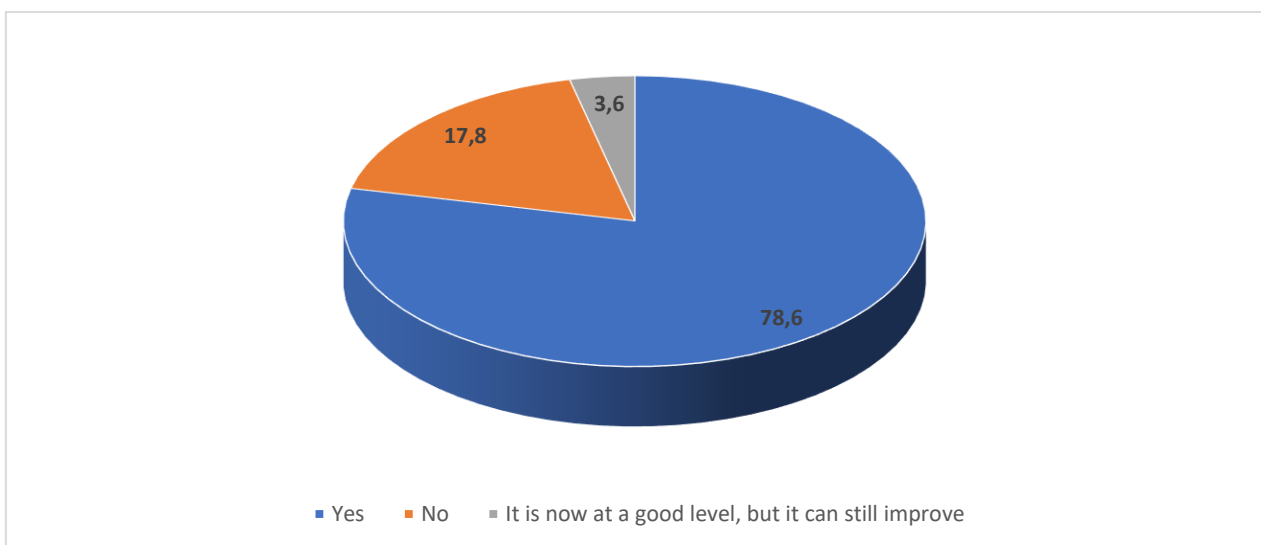


Fig. 8. Assessment the quality and applicability of digital resources and materials for students with disabilities, in %

The majority of responders claim that there is a clear necessity of improving the applicability and accessibility of digital materials and resources to be adapted for students with disabilities (78,6%). At the same time, another almost 20% (17,8%) felt that the materials available were of good quality, but could still be further improved and only 3,6% consider that the current quality of materials is good and therefore, it does not need to be upgraded.

The opinion of students on the quality of the educational materials and its adaptation is collected through the following question “Is it necessary to develop high-quality digital educational content that is brand new and aligned with curriculum standards?”. The obtained results indicate unambiguously that university students in Bulgaria found the necessity of developing new content appropriate for digital learning and digital environment (Fig.9).

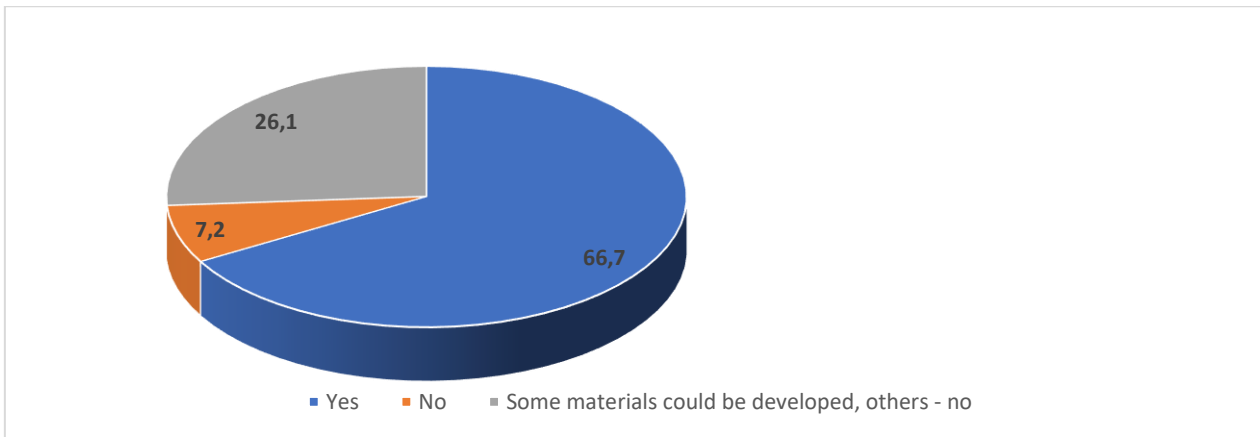


Fig. 9. Assessment the necessity of the development of brand-new digital content of educational materials, in %

When we consider digitalization, the problem for protection of personal data remains one of the important topics that has to be paid special attention, considering the speed of development of ICT, including the possibility of emergence of new threats and sophistication of hacker attacks. The answers of the question “Is it important to increase measures to protect students' personal data and ensure the security of online platforms?” presents the understanding of students for further development and guaranteeing protection of the personal data (Fig. 10).

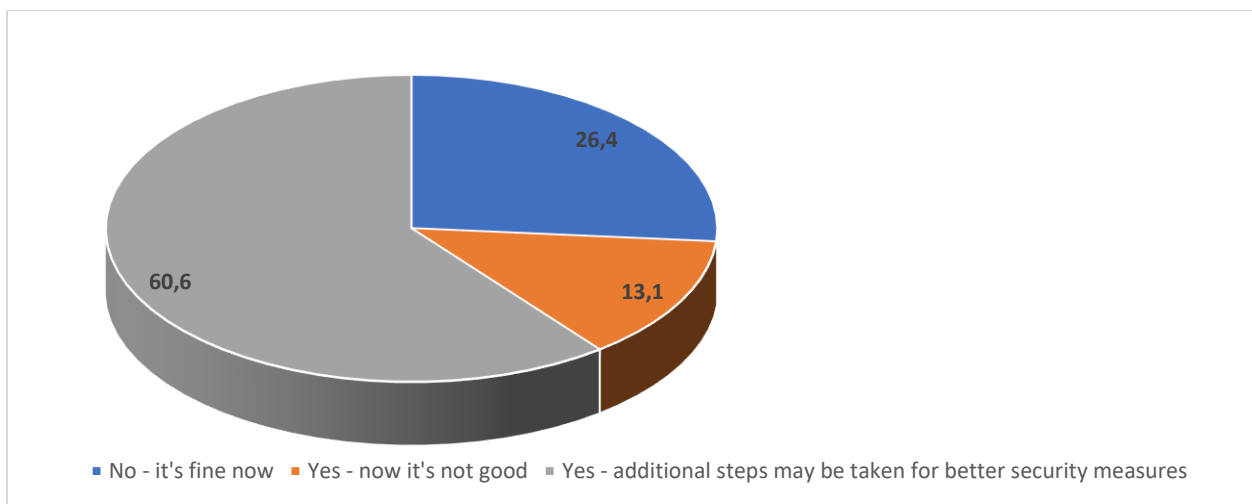


Fig. 10. Assessment the level of personal data protection of university students in digital environment, in %

As it can be seen from the figure, the majority of responders (60,6%) admit that additional steps for better security measures in digital environment could be taken. This result is in line with the responsible understanding

that cyber security must be seen as a continuous improvement process, parallel to the development and advancement of ICT technologies. At the same time 26,4% from our responders claim that the universities put enough effort into securing personal data and the current state of the systems is good enough.

Results, obtained through the question “Is it necessary to develop and improve hybrid learning models that combine both face-to-face and online elements?” clearly draw the expectation of university students (Fig. 11). The majority of them (almost 80%) find the future development namely in hybrid learning, combining the advantages of different forms to achieve high quality education in compliance with the new technologies and business requirement.

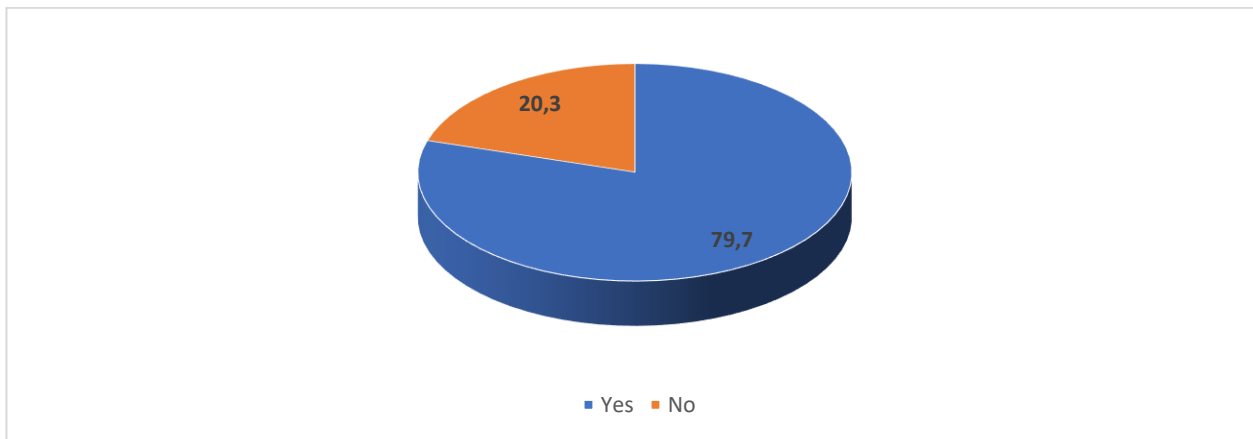


Fig.11. The attitude of students to hybrid learning process (both in traditional and digital environment), in %

Next question is the following: “Do student assessment methods need to be revised and refined to align with the positives and negatives of online learning?” and it is not surprising the fact, that the majority of responded students answer with “yes” (76,1%) versus only 23,9% whose answer is “no”. Therefore, it would be useful to come up with a comprehensive toolkit related to ensuring a fairer assessment of knowledge in digital evaluation process.

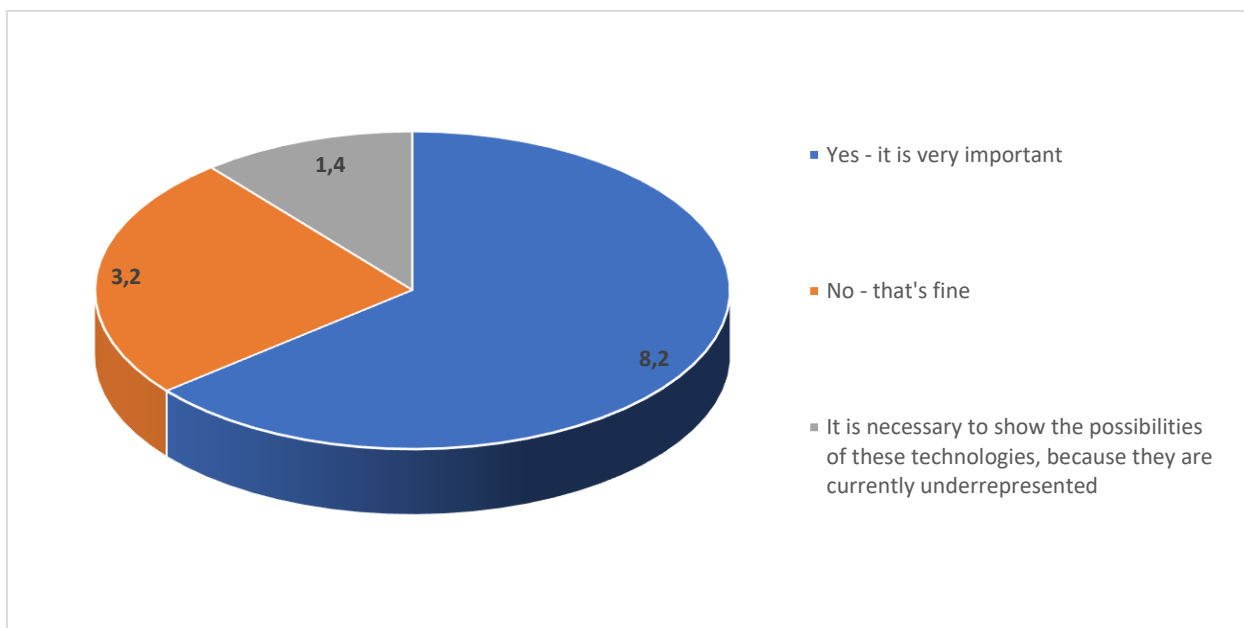


Fig.12. Further adoption of innovations in education process, in %

The final question collects information on the students' opinion for the further implementation of innovations in digital learning process. The majority of responders answered positively (almost 80% in total) to the question „Is there a need to focus on additional innovations in educational technology, including gamification, virtual reality, etc.?“. For almost half of the responders (47,5%) the innovations in digital learning process are very important aspect of the education. At the same time 31,7% of responders consider that these new technologies are poorly implemented at the moment and have to be further integrated in the learning process. Only 20,8% think that current state of play is fine and there is no need to be improved (Fig. 12).

In summary of the presented results of the empirical research, it should be said that students generally positively evaluate the efforts of universities to digitize the educational process. At the same time, some aspects of the educational process - such as the assessment in a digital environment, or the provision of administrative services - such as the application for dorm accommodation, which should be improved, are outlined. However, the need to make constant efforts to protect personal data and provide quality educational digital content is considered.

5. Identification of workable indicators for the assessment of the effective level of digitalization in HEIs

Based on the results and analysis of the research as well as authors study of different processes and systems of the universities in terms of digitalization, it could be identifying the following indicators for the assessment of the effectiveness of digitalization in HEI:

5.1. Online learning platforms adoption

The extent to which the university has adopted online learning platforms like Learning Management Systems (LMS). Online Learning Platforms Adoption refers to the incorporation and utilization of digital platforms designed to facilitate teaching and learning activities in higher education institutions. Common examples of these platforms include Moodle, Canvas, Blackboard, Sakai, and others. These platforms serve as centralized hubs where it can be organized course materials, facilitate communication, and administer assessments. Higher adoption of online learning platforms can streamline administrative tasks for instructors, making it easier to manage course materials, communicate with students, and assess learning outcomes. At the same time online platforms offer students greater flexibility in accessing course materials and participating in learning activities, potentially accommodating diverse learning styles and schedules. By tracking usage metrics and engagement levels on the online platform, university staff and managers can make data-driven decisions to improve teaching practices, allocate resources effectively, and enhance the overall educational experience for students.

The usage metrics such as course enrollment, content creation, student engagement, and assessment activities can indicate the level of digital integration in the teaching and learning process. Course Enrollment: This metric measures the number of students enrolled in courses offered through the online learning platform. Higher enrollment numbers typically indicate greater adoption and utilization of digital platforms across the university's curriculum. Content Creation: It evaluates the extent to which instructors are utilizing the platform to create and distribute course materials such as lecture slides, readings, videos, quizzes, and assignments. Metrics might include the number of new content uploads, types of content shared, and frequency of updates. Student Engagement: This metric assesses the level of student interaction and participation within the online learning environment. It could include indicators such as discussion forum activity, participation in virtual classrooms, and submission of assignments. Assessment Activities: It evaluates how extensively assessments, such as quizzes, tests, projects, and assignments, are administered and graded through the online platform. Metrics might include the number of assessments conducted online, variety in assessment types, and timeliness of feedback provided to students.

5.2. Digital resources availability

Availability and accessibility of digital resources such as e-books, online journals, databases, and multimedia materials and other digital assets, which are accessible to students, academic staff, and researchers through the university's library and online repositories.

Metrics for assessment of this indicator could be the following: quantity – by measuring the total number of digital resources available within the university's library and online repositories. It includes the total count of e-books, online journals, databases, and multimedia materials accessible to users; Coverage of digital materials: It evaluates the breadth and depth of subject coverage across different disciplines and fields of study. The richness and diversity of these resources can reflect the institution's commitment to digitalization in supporting research and academic activities; Accessibility and usability: the ease of access and usability of digital resources, including user interface design, search functionality, navigation tools, and availability of user support services. Here have to be added materials adopted for the needs of university students with disabilities; Statistics: Tracking usage statistics such as downloads, views, citations, and interactions with digital resources provides insights into the popularity and relevance of specific materials among users.

5.3. Available technology infrastructure

Available technology infrastructure refers to the physical and virtual resources, including hardware, software, networking capabilities, and support services, that are accessible to students, faculty, and staff within the university ecosystem to enable effective utilization of digital technologies. This indicator assesses the adequacy and accessibility of technological resources and support systems within a university to facilitate teaching, learning, research, and supportive administrative activities. It measures the quality and robustness of the technology infrastructure including network bandwidth, Wi-Fi coverage, computer labs, and availability of digital tools for students and faculty. A reliable and up-to-date infrastructure is essential for facilitating digital learning, research, and administrative tasks.

The indicator could be measured by the following metrics: Coverage and Accessibility: assessment the accessibility of technology infrastructure across different campus locations, including classrooms, laboratories, libraries, study areas, administrative offices, and remote learning environment; Reliability: it assesses the reliability, speed, and performance of technology infrastructure components such as network connections, hardware devices, and software applications to ensure uninterrupted access to digital resources and services; Scalability and Future Development: This metric examines the scalability and capacity of technology infrastructure to accommodate growing user demands, technological advancements, and emerging trends in digitalization, ensuring long-term sustainability and future readiness; User satisfaction and feedback: gathering feedback from students, both academic and administrative staff through surveys, focus groups, and feedback mechanisms helps in assessing user satisfaction levels, identifying areas for improvement, and addressing specific needs and preferences related to technology infrastructure.

5.4. Virtual collaboration tools usage

Utilization of virtual collaboration tools such as video conferencing platforms, online project management tools, and communication platforms. These tools enable remote collaboration among students and staff, promoting teamwork, communication, and productivity. Virtual collaboration could be implemented using: Video Conferencing Platforms: Examples include Zoom, Microsoft Teams, Google Meet, and Cisco Webex. These platforms enable real-time audio and video conferencing, screen sharing, chat, and collaboration on documents and presentations; Collaborative Document Editing Tools: Platforms like Google Docs, Microsoft Office Online, and Dropbox Paper allow multiple users to collaborate on documents, spreadsheets, presentations, and other files simultaneously, facilitating collaborative editing and version control; Instant Messaging and Chat Applications: Tools such as Slack, Microsoft Teams, Discord, and WhatsApp provide instant messaging, group chat, file sharing, and integration with other productivity apps, enhancing communication and collaboration among team

members; Project Management Software: Platforms like Trello, Asana, Basecamp, and Jira enable teams to plan, organize, track progress, assign tasks, and collaborate on projects using visual boards, task lists, timelines, and workflow automation feature; Virtual Whiteboarding Tools: Applications like Miro, MURAL, and Jamboard allow users to create and collaborate on digital whiteboards, diagrams, mind maps, and visual presentations, facilitating brainstorming, ideation, and collaborative problem-solving.

5.5. Integration of data analytics

This indicator assesses the extent to which a university utilizes data analytics techniques and tools to gather, analyze, and derive insights from various sources of data across academic, administrative, and operational domains. Adoption of data analytics tools and techniques for decision-making processes such as student performance analysis, course optimization, resource allocation, and strategic planning. Leveraging data analytics can enhance operational efficiency and effectiveness in various aspects of university management.

Integration of Data Analytics refers to the incorporation of data analytics methodologies, technologies, and practices into the university's decision-making processes, academic programs, research endeavors, student support services, and administrative operations to drive insights, improve performance, and enhance outcomes. This involves collecting, organizing, and managing diverse sources of data generated within the university ecosystem, including student information, academic records, research data, financial transactions, institutional operations data, and external data sources. This indicator includes Data analysis and modeling, Data Reporting, Predictive Analytics and Machine Learning.

5.6. Electronic Document Management

Implementation of electronic document management systems (EDMS) or digital repositories for storing, organizing, and managing administrative documents and records electronically. It assesses the extent to which a university has implemented digital systems and processes for the creation, storage, organization, retrieval, sharing, and management of electronic documents and records across various academic, administrative, and operational functions. EDM refers to the systematic management of electronic documents and records throughout their lifecycle, from creation or receipt to disposal or archiving, using digital technologies and tools to improve efficiency, accessibility, security, and compliance. This includes digitizing paper-based documents, enabling electronic signatures, and ensuring document version control and access permissions.

Metrics for assessment could be the following: adoption and utilization of electronic document management systems and tools across academic departments, administrative units, and operational functions within the university; Accessibility and usability: It assesses the ease of access, navigation, and usability of electronic document management systems for users, including students, administrative and academic staff, and external stakeholders, through user satisfaction surveys, feedback mechanisms, and usability testing; Efficiency and productivity - the impact of electronic document management on workflow efficiency, productivity gains, time savings, reduction in paper-based processes, and elimination of manual tasks such as printing, copying, filing, and physical document storage; Compliance and Risk management - the degree to which EDMs comply with relevant legal, regulatory, and institutional requirements, including data protection laws, records management policies, retention schedules, and audit trails; Cost Savings and ROI - cost-effectiveness and return on investment (ROI) of electronic document management initiatives, including savings in paper, printing, storage, and administrative overhead costs, as well as improvements in operational efficiency and productivity.

5.7. Digital marketing and recruitment efforts

The university's digital presence and activities in marketing, recruitment, and student engagement through social media, websites, online advertisements, and virtual events. This indicator assesses the effectiveness of a university's digital strategies and initiatives aimed at attracting, engaging, and converting prospective students and stakeholders through online channels and platforms. Digital Marketing and Recruitment Efforts refer to the strategic use of digital channels, technologies, and tactics to promote the university's brand, academic programs,

campus culture, and unique value proposition to prospective students, parents, alumni, business, partners, and other stakeholders.

Components of the digital marketing could be: Online Presence and Branding – establishing a strong and cohesive online presence through the university website, social media profiles, blog posts, videos, virtual tours, and other digital platforms to showcase the institution's brand identity, values, and offerings; Search Engine Optimization – to optimize the university's website and digital content for search engines, improving visibility, organic traffic, and search engine rankings for relevant keywords and phrases related to academic programs, campus facilities, and student life; Content Marketing and Social Media – creating and sharing valuable, informative, and engaging content across social media platforms, blogs, podcasts, webinars, and other channels to attract and engage prospective students, parents, influencers, and other stakeholders; Email Marketing and Automation – to nurture relationships with prospective students, provide personalized communication, deliver targeted messaging, and guide them through the admissions funnel from inquiry to enrollment using automation tools and drip campaigns; Paid Advertising - such as pay-per-click (PPC) ads, display ads, social media ads, and re-marketing campaigns are deployed to reach specific audience segments, retarget website visitors, and drive traffic, leads, and conversions for key recruitment goals; Data Analytics and Performance Tracking – to monitor and analyze the performance of digital marketing campaigns, track key performance indicators (KPIs), measure ROI, and optimize strategies based on data-driven insights and actionable analytics. Effective digital marketing strategies can help attract prospective students, engage current students, and strengthen the university's brand reputation.

5.8. Cybersecurity policy

Implementation of robust cybersecurity measures to safeguard digital assets, sensitive information, and personal data against cyber threats and breaches. This indicator assesses the effectiveness of a university's strategies, policies, and practices in protecting digital assets, information systems, and sensitive data from cybersecurity threats, vulnerabilities, and breaches.

Metrics of assessment under this indicator could be the following: Security posture and maturity - assessing the university's overall cybersecurity posture and maturity level based on cybersecurity frameworks such as NIST Cybersecurity Framework, ISO/IEC 27001, CIS Controls, and maturity models like Cybersecurity Capability Maturity Model (C2M2); Incident Response Time and Effectiveness – measuring the average time to detect, respond to, contain, and recover from cybersecurity incidents, breaches, and data breaches, and evaluating the effectiveness of incident response procedures and mitigation efforts; Compliance and regulatory adherence: Ensuring compliance with relevant Bulgarian laws and European regulations, and industry standards such as GDPR and other, and assessing adherence to compliance requirements through audits and assessments; Security Controls: assessing the effectiveness of security controls, patches, updates, and vulnerability management processes in mitigating known vulnerabilities, patching critical vulnerabilities, and reducing the attack surface; User Awareness and Training: Measuring the effectiveness of cybersecurity awareness training programs, phishing simulations, security quizzes, and user feedback surveys in improving user awareness, behavior, and adherence to security policies and best practices. Regular security audits, compliance with data protection regulations, and cybersecurity awareness programs are crucial for maintaining a secure digital environment.

5.9. Feedback mechanisms and continuous improvement

Availability of feedback mechanisms such as online surveys, evaluation forms, and digital suggestion boxes to gather input from stakeholders including students, academic and administrative staff. It evaluates the effectiveness of mechanisms and processes implemented by a university to gather, analyze, and act upon feedback from stakeholders regarding various aspects of digitalization efforts.

Metrics for its evaluation could be the following: Feedback response rates – the percentage of stakeholders who provide feedback in response to feedback requests or surveys. Higher response rates indicate greater engagement and participation in feedback mechanisms; Feedback satisfaction scores: the satisfaction levels admit by users

in terms of accessibility, ease of use, responsiveness, transparency, and perceived impact on addressing their concerns and suggestions; Improvement Culture - the development and promotion of a culture of continuous improvement within the university, where feedback is valued, encouraged, and integrated into decision-making processes at all levels of the organization. Monitoring of feedback and subsequent improvements demonstrate a commitment to enhancing the digital experience and addressing emerging needs.

5. Conclusion and recommendations

Universities should by default be institutions where knowledge is preserved during centuries and shared by new generation of young people, eager for study. In this sense, higher education institutions are the guardians of traditions. At the same time, however, they are called to prepare the new generation for the new challenges of the economy and the demands of business. Which means that in addition to preserving traditions, they must also be open to the latest technologies.

The digitization of higher education and, in particular, education process at a university is an extremely complex process, which, among other things, should guarantee the provision of quality education. From this point of view, digitization in universities should not be seen only as the transfer of activities and services from a traditional to a digital environment. Here comes precisely the moment for the importance of evaluating the effectiveness of the level of digitization in universities. For this purpose, we have developed 9 complex indicators with their evaluation metrics, through which a clear idea can be given of the level of effectiveness of digitization in higher education institutions.

Based on an empirical survey among 360 students, we established their assessment of the current state of the system in Bulgarian higher education institutions, and after a thorough analysis of the collected information and additional research, we developed and presented the following indicators for evaluating effectiveness, which have to be assessed at the same time in order to analyze properly the achieved effective level of digitalization: Available online platform and their adoption in university activities; Availability and accessibility of digital resources; Available technology infrastructure; Usage of virtual collaboration tools; Integration of Data analytics; Electronic document management; Digital marketing and recruitment efforts; Cybersecurity policy and Feedback mechanisms and continuous improvement.

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Influence of Artificial Intelligence on Transformational Leadership

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Abstract. Artificial Intelligence (AI) recently plays a major role in the working world. AI in few years will be inevitable in all the businesses and services. AI also plays a virtuous role in supporting Human Resource Management. Most people fear that AI will cause them unemployment, but truly, AI has the capacity to build more jobs in the near future as AI will not remove workers from their jobs, but it will reduce monotony and frees up employees to perform more complex tasks. Transformational leadership are always ready for a positive and innovative change in the organization. By leveraging Artificial Intelligence technologies, leaders can become more transformational, foster a culture of innovation, and drive successful organizational transformations. This article aims at analyzing how artificial intelligence plays a role in enhancing transformational leadership. This paper aims at providing a comprehensive review of how artificial intelligence impacts transformational leadership. The results of the study concluded that AI technologies can help leaders to become more transformational thereby empowering their employees and become a reason for successful organizational changes. This article also helps in gaining new insights into how AI can play a role in enhancing transformational leadership in an organization.

Keywords— Artificial Intelligence, Automation, Innovation, Technology, Transformational Leadership.

INTRODUCTION

Artificial Intelligence (AI) is the recent advancement in technology that plays a crucial role in businesses and support various tasks in organizations. AI is a newly developed technology that requires human intelligence for its proper execution. AI is developing systems that will perform tasks with the aid of human assistance AI has the potential to drive transformations in business and leadership as well. AI technology is transforming the ways in which a business operates but it has a significant effect on leadership. AI mainly supports transformational leadership in an organization. Transformational leadership is the style of leadership that inspires, builds trust, and motivates innovation and change in the organization.

As transformational leadership majorly relies on communication, collaboration, and innovation, and AI has the potential to enhance innovation capability, the communication and collaboration framework within an organization and hence AI plays a significant role in supporting Transformational leadership. AI will give even more importance to transformational leadership and so, if leaders integrate AI into their organization, they will be able to engage their employees better and promote good learning and development among their team. The other way round, when AI needs to be implemented successfully, it needs the support of transformational leadership. When transformational leaders support AI and implement them in their operations, they can optimize productivity

AI can support transformational leaders in making much more informed decisions which eventually leads to creation of a positive as well as a productive work environment. AI helps leaders to reduce complexity in their tasks and thereby spend more time in critical and important. AI also facilitates collaboration and communication between leaders and their team members thereby facilitating personalized communication which creates more meaningful relationships between leaders and his team members. AI also helps in promoting employee empowerment by fostering innovation. They allow automation of routine tasks and allow employees to focus on more creativity and innovation which benefits the employees and the organization as a whole. Various researches have also found out that AI plays a moderating role between Transformational leadership and innovation. AI and transformational leadership when worked together in conjunction, it can improve the quality and the quantity of ideas generated by their team members. AI helps transformational leaders meet the unique ideas of the teams and helps individuals focus on their strengths which will lead them to higher levels of innovation and creativity. AI

when integrated with transformational leadership, it facilitates a collaborative innovative environment by promoting knowledge sharing and idea evaluation.

This article aims exploring how artificial intelligence plays a role in assisting transformational leadership and further intends to extend the insights on this upcoming research topic. The next section provides with the objective of the study and the following section presents the methodology of the study. Then, the study on existing literatures are presented and at last the literature reviews are discussed and the study has been concluded with the findings from the secondary data analysis.

OBJECTIVES OF THE STUDY

- To conduct an intensive literature review on the impact of Artificial Intelligence on Transformational Leadership.
- To analyze the role played by artificial intelligence in supporting transformational leadership and explore the relationship between these two.

RESEARCH METHODOLOGY

The study is descriptive in nature. It is wholly dependent on secondary data collected from previously published research articles and blogs. Conclusion for the study was extracted from the data collected through secondary literature review. The results from this study will contribute to the discussions in-progress on the role of Artificial Intelligence in supporting transformational leadership.

LITERATURE REVIEW

Transformational Leadership

Bernard M. Bass (1985) is said as the father of transformational leadership and identified four elements of transformational leadership namely intellectual stimulation, idealized influence, inspirational motivation, and individualized consideration. Bono, Ilies (2006), states that when transformational leaders display more of charisma are effective in creating more positive work environment and thereby leading to better performance and satisfaction. When leaders display transformational leadership, it is said to affect the employee's organizational commitment and further tends to psychologically empowers them, . Transformational leadership is essential for leaders for them to effectively respond to dynamic organizational situations and achieve optimum results, and Judge & Piccolo (2004) also argues that transformational leadership must be adopted by leaders if they want to improve organizational results. Bernard Bass (1985) puts forward his thought that is the organizations need to survive in the longer run, then its leaders must adopt a transformational style of leadership as it helps organizations to adapt to the dynamic business environment by enhancing creativity and innovation among the employees.

Artificial Intelligence

AI tools such as chatbots and predictive analysis helps in enhancing employee support in organizations. Mary Lacity et.al. (2018), insists that AI tools help in making data driven decision making and making employee experiences more personalized that improves the role of HR as a strategic partner in the organization. AI can positively impact the HR functions by eliminating repetitive and monotonous tasks and improving employee engagement which is very vital for the employee productivity, Kannan and Msila (2021) argue that through increased job satisfaction and increased opportunities for collaboration, AI tends to have a positive impact on the employee engagement. AI also helps leaders in personalizing and customizing training programs according to the varying needs of employees as said by Quaquebeke et al. (2019). AI is a major support to employee learning by making their learning experiences more personalized and engaging for the employees, and provide personalized suggestions and feedback for the employees thereby creating a positive and supportive work environment,. AI is so much personalized to employees as they help employees in identifying their strengths, weaknesses and also receive targeted support and feedback about their performance,

Artificial Intelligence and Transformational Leadership

According to Kutsyuruba et al., (2019) AI technologies provide leaders with real-time data and decision support that will enhance transformational leadership, by providing alternative courses of action that even the leaders have not considered. As stated by Sull et al. (2019), predictive analytics helps leaders to forecast future trends and also identify potential areas for further growth and innovation. Akhar et al. (2020) examines the benefits of using AI in empowering the employees and enhancing innovation capabilities. The authors argue that automation of routine and monotonous tasks allows leaders to focus on more critical areas and benefit the organization on the whole. Parry et al (2020) explores on how AI can assist leaders in identifying data patterns which makes it possible for them to gain better insights into the organizational processes and employee performance.

Schlusser & Storniolo (2018) discuss the ethical implications of using AI in leadership. The researcher proposed that the leaders must be mindful of these concerns so that AI should be used in responsible and an ethical way. AI positively impacts transformational leadership by enhancing decision-making, increasing creativity, and strengthening communication as pointed by Raza & Imran (2020) in their study. In exploring the role of transformational leadership in AI enabled organizations, Khan & Rahman (2019) found that transformational leadership is necessary for building trust for adopting AI in the organization and motivate employees to celebrate new technology and find various ways to utilize it in an effective way.

According to Kumar & Gursoy (2021) , transformational leadership is said to foster a positive attitude towards enabling AI in an organization which leads to higher levels of usage and acceptance. AI can also be used to develop personalized leadership programs that helps the leaders to identify the strengths and weaknesses of leaders with which the leaders can enhance their strengths and promote innovation within an organization,. A meta-analysis by Duan et al., (2019) stated that AI can enhance decision making by leaders by enabling them to make informed data driven decisions based on data analysis and predictive analytics. A literature analysis by Vaiman & Karia (2018) found that AI has the capacity to transform leadership practices, enabling leaders to become more responsive, creative, and adaptable to changes which helps organizations to remain competitive in this rapidly changing business environment.

According to Hackbarth et al., (2019) helps in automating repetitive and monotonous tasks which provides them the time to focus on critical and important tasks, for which transformational leaders should be capable of understanding the technology and use it effectively as well as maintaining ethical and social responsibility,. In exploring the implications of AI for leadership, Myers (2020) suggests that leaders should work collaboratively with AI and create a workplace culture that values and supports innovation, creativity and informed decision making. Huang (2019) argues that transformational leadership require a growth mindset that supports continuous learning and improvement as well as empowering employees to adopt the culture of AI.

AI and transformational leadership when used collaboratively plays a major role in gaining a competitive advantage for the organizations,. AI supports innovation. As proposed by Yao et al., (2020), AI and transformational leadership can work collaboratively to improve the quality and quantity of new ideas generated by teams and combining transformational leadership and AI will help create powerful and a dynamic approach to innovation,. Reeves, Szlezak & Swartz (2019) argue that AI does not replace humans in decision making but they are act as an augment to human decision-making.

DISCUSSIONS

From the intensive literature analysis conducted, the researcher found that AI in combination with transformational leadership promotes innovation and creativity in an organization. It was also found that AI will help in creating powerful and a dynamic approach to innovation. AI and leadership majorly play a vital role in fostering innovation in an organization by enabling the team members to make innovative ideas and work further on it. These findings were in consistent with Akhar et al. (2020) and Fong & Boon (2019).

The study also found out that AI promotes automation of routine and monotonous tasks and gives time for leaders to focus on more critical and vital areas and benefit the team as well as organization as well as AI supports leaders in decision making by enabling them to make informed data driven decisions and predictive analysis. The study coincided with the studies made my Duan et al. (2019), Hackbarth et al., (2019) and Akhar et al. (2020).

The author found about the ethical implications of using AI in leadership. While combining AI and leadership, AI should be used in an ethical and responsible manner so that there will not be any ethical concerns arising out of implementing AI in leadership. This can be made possible only of the leaders and the employees understand the technology and use it effectively by maintaining a social and ethical responsibility. These findings

are in agreement with Schlosser & Storniolo (2018) and Kanwar & McLeod (2019). The researcher also found that using AI in transformational leadership and thereby implementing AI in the whole organization, it enables organization to gain a competitive advantage for the organisations.

CONCLUSION

In conclusion, the collaboration of AI with transformational leadership supports various organizational tasks such as decision making, promoting innovation and creativity, earning better insights into the organizational processes, and gaining competitive advantage for the organization. The adoption of AI has not only been advantageous but also has brought new challenges to leaders. Transformational leaders who are proactive and utilize AI in a good and ethical way can take organizations to greater heights. Overall, the success of AI adoption and transformational leadership is dependent on the leader's ability promote a culture of innovation in the organization that embraces change and providing a clear sense of direction for the organization.

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ARTICLES FOR FACULTY MEMBERS

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Leveraging ChatGPT in public sector human resource management education

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ABSTRACT

The potential benefits and challenges of AI in the workplace are documented with public service facing a particular choice to leverage this tool to better communities. This article explores the use of generative artificial intelligence (AI) tools in public service education. As students prepare to enter public service, they need to gain the skills to manage the advantages and threats of AI. This article explores one attempt to prepare students for the intersection of public service and AI using a human resource management course. This article explores the use of ChatGPT, as a generative AI tool, for both instructors and students across the academic year. We explore the pedagogical strategies involved and share outcomes and lessons learned for future integration of AI in the classroom.



KEYWORDS

AI; ChatGPT; human resource management; public service education; reflective learning and teaching

AI has the potential to radically change the efficiency and effectiveness of public goods and services delivery across multiple sectors including transportation, taxes, healthcare, and education (World Economic Forum, n.d.). With the addition of new artificial intelligence (AI) tools, the practice of work is inherently changing (Berryhill et al., 2019). Students are facing a workplace that may integrate both basic and generative AI tools in a multitude of ways. In public service, AI has been suggested as a potential virtual assistant for public servants and community members seeking help (Berglind et al., 2022), as an evaluator for distributing publicly supported benefits (Martinho-Truswell, 2018), and as a risk-assessment tool for air cargo transportation (Berryhill et al., 2019). Educators in public service are tasked with the opportunity to prepare the next generation of public leaders by introducing important theories and practices and providing a space to explore the nexus of the two areas. With this charge in mind, public service education and educators should consider how to incorporate the use of AI into their curriculum, to better prepare students for the workplaces of tomorrow.

Generative AI and public service

AI tools have existed for some time, with research into this topic starting in the early 1950s (Anyoha, 2017). The reality of AI was realized in the late 1990s with speech recognition

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software (Anyoha, 2017). These early AI tools, often referred to as traditional AI, are designed to perform tasks based on a specific set of inputs and within programmed boundaries (Heaslip, 2023). While the technology can learn from the data and even make predictions, no new strategies are invented. For example, a very traditional AI, Grammarly, uses the rules of the specified language to check for proper spelling, grammar, and tone within a provided text. On the other hand, generative AI, which has recently started to become more publicly available, generates new information based on the data provided, including new strategies for solving problems (Heaslip, 2023). The introduction of these generative AI tools, like ChatGPT and Gemini, shifted the nature of education and the expectations around workplaces of the future. Within education, universities began writing policies around the use of AI in the classroom. Collaboration between institutions of higher education and AI developers to expand both faculty and student use of and understanding of AI has emerged as demonstrated by the recent partnership between Arizona State University and OpenAI (abc15.comstaff & Associated Press, 2024). Students and instructors are benefiting from the tools of AI, using the technology to assist in brainstorming, editing, problem-solving, and data analysis (Fui-Hoon Nah et al., 2023).

Additionally, researchers and practitioners are identifying the importance of understanding and leveraging AI in work and public service (National Academy of & Public Administration, 2019). With the ability of AI to rapidly process data, sift through multiple contexts, and streamline repetitive and basic tasks, public servants may be able to focus more on the quality of services provided as the technology helps mitigate the growing quantity of tasks (Martinho-Truswell, 2018). However, AI inherently poses risks for public servants wanting to use the technology ranging from deepening the digital divide to concerns about ethics, discrimination, misinformation, or disinformation (i.e., hallucinations), privacy of information shared, and limiting an individual's agency to choose (Fui-Hoon Nah et al., 2023; National Academy of & Public Administration, 2019).

Teaching students how to navigate the benefits of AI while addressing and avoiding the pitfalls should be a topic of discussion and exploration in public service education. As public affairs educators, we should be providing students with the opportunity to experiment with AI in a controlled environment, help students construct their mental models for engaging with AI, and create opportunities to critically evaluate the inputs and outputs of AI technology within the context of public service. Our teaching should move beyond placing limits on students, instead, we should focus on teaching students how to responsibly and ethically use a tool that is becoming more ubiquitous over time (Chiu, 2023; Lambert & Stevens, 2023). One area where public service education programs may find success in introducing AI into their curriculum is human resource management.

In this article, we review how both instructors and students engaged with ChatGPT, the justification behind the decision to engage, and our pedagogical approach (which reviews the audience, the framing and emphasis, and the topics covered). We conclude by sharing both lessons learned and some outcomes for the students and instructors.

Implementing AI in an HRM course

This article describes the approach taken by instructors over two semesters to integrate AI use into their work and the class work of students for a survey course on human resource management (HRM) in response to student questions and changing

practices in public service. Human resource management (HRM) professionals are expected to engage in multiple aspects of talent management, including recruitment and retention, workforce planning, and development and implementation of workplace policies and procedures. HRM professionals are also expected to participate in and connect their work to the strategic vision and plan for their organization. Many of these elements have relied on some form of non-generative, or traditional, AI to support hiring, provide basic user support, analyze performance metrics, and visualize data (Afzal et al., 2023; Berryhill et al., 2019). With the introduction of generative AI to the public in the early 2020s, the potential for non-generative AI to be eventually subsumed into HR-focused generative AI tools exists (Afzal et al., 2023). As such, the decision was made to focus on generative AI tools to ensure students were prepared for any future AI interactions in the workplace. We developed weekly AI demonstrations and student activities to model how to integrate AI into HRM work. For example, during one demonstration instructors modeled how ChatGPT can serve as a coach for employees going through the onboarding process by providing both guidance and opportunities to check for understanding around organizational policies. Students had the opportunity to experiment with this technique in the following week's demonstration. The weekly practice provided students the opportunity to see how AI would work within their HRM practices. Several students reported pulling AI into their workplace during the semester to assist in writing job descriptions, updating organizational policies and practices, and brainstorming solutions to HRM-related challenges.

The context

This course, taught over two semesters by the lead author (with assistance in the first semester from the coauthor), provided 24 students enrolled in either a master's in public administration (MPA) or master's in health administration (MHA) the opportunity to explore the application of AI in their workplaces and within the HRM field more generally. Students from both programs tended to be mid-career professionals who work full-time in addition to attending night classes as part of their graduate education. In terms of class make-up, most students were residents of the United States, with about 20% of the students across both semesters coming from outside of the U.S. Additionally, the course leaned majority female (just over 60%) and students of color (about 60%). Students had a variety of educational backgrounds in public administration before their acceptance into the MPA and MHA programs and work experience spanning across the state and local government service, nonprofit and community work, and healthcare sectors. Additionally, the HRM course, a required course for all students in the MPA/MHA degree track, is taught in the first two semesters of the required sequence of core courses (ranging from data analysis to organizational behavior), so many students are engaging with this content in addition to familiarizing themselves with graduate school expectations. The course was developed under the guidance of the lead author using philosophies pulled from ungrading, project-based learning, and reflective teaching. During the first semester, the co-teacher assisted in developing the context for the semester-long simulation and provided weekly insights for the assigned topic of study, due to his extensive HRM experience and professional background in the healthcare industry.

During the first few weeks of the school year, multiple students asked many questions about the role of AI in relation to different elements of HRM being studied, from job design and analysis to strategic human resource management. From the questions being asked, it was clear that students were aware of the benefits and threats posed by AI in HRM and public service in general. It was determined that one way to support student learning was not only to provide opportunities for students to learn about the use of AI through preparation materials and weekly class lectures and discussions, but to demonstrate how students may leverage AI in future HRM-related positions. We also incorporated AI into our teaching preparation to better understand some of the issues that may arise when using AI, both technically and ethically.

In our class, we invited students to use the AI tool ChatGPT. The choice to use ChatGPT was based on three elements: the user-friendly interface, the documented issues with other generative AI tech at the start of the class (Metz, 2023), and the free user version students could easily access (to avoid placing any additional financial or technological burdens on students). No additional materials (i.e., textbooks, podcasts, articles, etc.) were provided as required reading, although a section on reading materials related to AI and HRM was curated for a stand-alone additional resources page provided for students who wanted to pursue additional learning. While we focused on ChatGPT due to the widely available and affordable nature of the product, we made sure to spend time reviewing other forms of AI as well, although students did not get instructor-directed or hands-on experience with these tools.

Pedagogical approach: reflective teaching and learning & inquiry-based learning

Reflection is a key to learning and provides an opportunity to reinforce knowledge and identify areas to improve (Moon, 2013). The course and instructor teaching philosophy draws on various concepts of reflective teaching and learning as well as inquiry-guided learning practices to center on four different elements of learning: preparation, participation, application, and reflection. Designed as a survey course of the fundamental elements of human resource management (HRM), the course centers on concepts of strategic HRM and reviews different HRM policies and processes. The course is a core class requirement for students in Master of Public Administration and Master of Healthcare Administration degree programs. Students enrolled in the two programs tend to be working professionals. Many students are currently working in public service or healthcare organizations and use the course as a sandbox to improve their skills and organizations. Additionally, the course emphasized concepts of accessibility, working to provide materials to students in accessible formats and at the lowest cost possible.

The course was structured to emphasize reflective practices for the instructors and reflective practices for the students, as both are part of the teaching and learning process. Reflective learning and teaching are focused on evaluating our behaviors and outcomes to improve the quality of both our teaching and learning over time (Ashwin et al., 2020). Reflective teaching and learning move from simply observing the outcomes to seeking to understand and apply the lessons learned from observation to improve our behaviors and increase our knowledge (Ashwin et al., 2020). The principles of reflective teaching, including active engagement, appropriate assessment, scaffolded and systematic development, and

application to professional experiences (Ashwin et al., 2020), are emphasized in the course design to cultivate a classroom culture of learning accountability and engagement. Reflection was encouraged for both the instructors and the students using reflective writing, feedback tools, and discussion.

In addition to the reflective teaching practices, the course was built around inquiry-based learning, using both problem-based and case study methods. Both methods center on student growth, either learning how to identify problems and provide potential solutions (Nilson, 2016) or generating experiences where students could identify areas for growth and personal application (Harrington & Simon, 2022). Per the suggestion of Ng et al. (2023), we focused on designing AI interactions and learning experiences focused on project-based learning where students could create authentic, meaningful artifacts and learn through collaboration.¹

Integrating ChatGPT into a HRM course

Before the semester, language was added to the course syllabus to encourage student use of ChatGPT and other AI tools in the course. The syllabus language (see Table 1) focused on students engaging with ChatGPT as a reference and editor, not creating original content. ChatGPT was integrated as a tool for both students and course instructors as explained below.

Table 1. Syllabus statement on AI in the classroom.

Acceptable and Unacceptable Use of AI
<p>When in doubt about permitted usage, please ask for clarification. The use of generative AI tools (e.g. ChatGPT, Dall-e, Grammarly, etc.) <i>is permitted in this course</i> for the following activities:</p> <ul style="list-style-type: none"> ● Brainstorming and refining your ideas. ● Fine tuning your research questions. ● Drafting an outline to organize your thoughts. ● Revising originally created language as part of the iterative drafting process. ● Checking grammar and style. <p>The use of generative AI tools <i>is not permitted in this course</i> for the following activities:</p> <ul style="list-style-type: none"> ● Finding information on your topic ● Impersonating you in classroom contexts, such as by using the tool to compose discussion board prompts assigned to you or content that you put into a Zoom chat. ● Completing group work that your group has assigned to you, unless it is mutually agreed upon that you may utilize the tool. ● Writing a draft of a writing assignment (unless explicitly indicated in the assignment description). ● Writing entire sentences, paragraphs, or articles to complete class assignments. <p>You are responsible for the information you submit based on an AI query (for instance, that it does not violate intellectual property laws, or contain misinformation or unethical content). Your use of AI tools must be properly documented and cited in order to stay within university policies on academic honesty. For example, OpenAI. (2023). <i>ChatGPT</i> (Mar 14 version) [Large language model]. https://chat.openai.com/chat.</p> <p>Any assignment that is found to have used generative AI tools in unauthorized ways will be subject to grading and other penalties, including being reported for academic dishonesty based on the instructor's discretion and the seriousness of the offense.</p>

¹For example, students participated in a pre- and post-survey about the larger class simulation and had the opportunity to participate in a weekly survey that reflected on the subject and the simulation design. At the end of the semester, both instructors met with the students one-on-one to review their learning, assign a grade, and reflect on ways to improve the course moving forward.

Student use and outcomes

In questions asked through class discussion and the written weekly reading logs, students indicated their desire to understand AI's basic functionality and how to apply this technology within HRM. Two example questions (below) reflect the range of AI awareness and understanding by the students:

- (1) "How can staff adapt to using artificial intelligence in the future?"
- (2) "How will standard practices, such as merit-based principles and practices change as technology increasingly replaces folks' skills and knowledge?"

Table 2 lists the required student activities and desired outcomes as well as how each activity worked to incorporate AI.

Analysis assignments

Students selected an organization to analyze over the semester and were given bi-monthly prompts to evaluate specific parts of the organization's HRM processes and policies. Analysis assignments were short 800–900 word papers analyzing policies around recruitment and selection, diversity, equity, and inclusion, and work-life balance that also identified environmental challenges to the current practices of the HRM policies and/or processes and offered suggestions for future implementation.

The instructors provided two specific assignments for students to apply their learning and explore the potential of generative AI (a sample assignment is found in the appendix).

Table 2. Student activities and outcomes.

Activity	Description	Desired Outcome
<i>AI Demonstrations</i>	Students explored different HRM tasks using ChatGPT, including creating an ethics "counselor" to help navigate ethical conundrums and generating content for onboarding training. Instructors magnified this exploration by demonstrating one way to complete the assigned tasks and to continue exploring this task beyond the provided project brief.	Students are given an opportunity to explore and engage in a hands-on experience with AI as it relates to stated HRM tasks.
<i>Analysis Assignments</i>	Students analyzed an organization of choice throughout the semester evaluating various HRM processes (see Appendix for example) while incorporating ChatGPT as a tool to generate HRM-related content.	Students are able to apply their theoretical knowledge within an organizational context while practicing important HRM skills (like writing job descriptions) using new AI technology.
<i>Class Discussions</i>	Students engaged in small and large group discussions on topics regarding AI and HRM.	Students were able to develop a deeper understanding of the benefits and challenges of implementing AI within the HRM and public service context.
<i>Reflective Writing</i>	Students used various forums to reflect, through writing, on their learning, the preparation materials, and their questions about AI, HRM, and related topics.	Students were able to improve their critical thinking skills and deepen their mastery of the subject while identifying ways AI can be implemented in public service HRM.
<i>Weekly Simulations</i>	Students participated in a semester-long simulation for one organization. As part of the simulation, students, using materials generated by AI, were asked to address various HRM challenges and provide solutions, which often required an assessment of the provided AI-generated materials.	Students had opportunities to apply their learning to a real-world context and identify larger, holistic connections between HRM practices.

For the first AI-based analysis assignment, students conducted a 30-minute job analysis interview with an employee in the organization they analyzed or with an employee in a partner nonprofit organization. After creating duty statements from the interview task, students used ChatGPT to generate a sample job description from the provided prompt and the table of duty statements. The original, generated output was part of the required submission materials. Students then edited the generated job description to reflect their understanding of the interviewee's job more accurately. Students also included a personal reflection on the assignment topic, the process, and the use of ChatGPT.

For the second analysis assignment using ChatGPT, students created a future policy for the organization they had analyzed throughout the semester (see appendix for assignment description). Students had to generate a summary of the policy they felt their organization needed to create, the environmental factors that could influence the policy implementation, and identify other implementation barriers. Students then had to generate a prompt for ChatGPT, which they submitted as part of the assignment. Students provided the original output from ChatGPT, an edited version of the policy, and a personal reflection on the assignment overall.

From both assignments, students reported their engagement with this assignment was a positive experience. Students discussed how using ChatGPT helped them identify areas they had missed in their analysis and thinking. Other students discussed how ChatGPT helped them become more confident in their writing. Many students reported they could envision using ChatGPT in their future work while some students reported they had already begun using ChatGPT in their work as a supervisor or manager from editing and producing summary reports to developing workplace policies.

I was most proud of coming up with a policy that I felt would be useful for employees and help individuals achieve a happier work-life balance. After conducting my interview earlier this semester, I learned about all the little factors involved in maintaining an organization . . . I could potentially incorporate this type of practice into my work by using the analytical skills that I developed in this project to analyze not only my work but also my references when completing assignments. I think this assignment helped me dive deeper into the resources I was provided with and gain a better understanding, as it was necessary to analyze this information thoroughly to develop a policy that had not yet been implemented within the given organization. – Student enrolled in MHA program.²

Discussions

As instructors, we engaged in weekly reflection as well. We met weekly as a team to review the previous course session, reflect on student questions from the reading logs (see the next section on reflective writing), review other reflection responses from students, and prepare for the next class session. We used the weekly reading log questions to customize the prepared lesson content to student concerns and ideas. In particular, the co-teacher with experience in the healthcare industry focused on providing a 10–20 minute perspective on specific questions that incorporated the instructor's experience and large group discussion activities.

²The IRB ethics committee waived the requirement for approval if students signed a consent form allowing the use of their words in an anonymized fashion. Students were presented with the opportunity to participate and share their words after the semester had ended to avoid any undue influence.

Semester-long simulation

Students engaged in weekly simulations facilitated during class-time. Students assumed the role of board members for Sunnyside, a nonprofit, midsize fictional hospital (semester 1), or community services nonprofit (semester 2). Sunnyside's relevant details, challenges, and community information were all drawn from public records for a similar hospital within the United States (semester 1) and from local nonprofit information (semester 2). Each week, the students, as a board, confronted specific challenges they needed to solve. Students were provided a scenario, needed information and materials like sample performance evaluation plans or job descriptions, and asked to produce a work product as a small group or class. For example, in Week 7, students updated Sunnyside's basic evaluation plan to one that was more comprehensive and integrated across all employee groups. During Weeks 13 and 14, students worked to develop contingency plans and policies around labor disputes and emergency management crises. Students also used the simulation to develop job interview questions and matrixes for a new Sunnyside CEO and create an onboarding plan for this new leader.

Reflective writing

Reflective writing encourages active learning and is a critical element in helping students enrolled in professional programs engage in deeper learning (McGuire et al., 2009). As part of the reading logs, students answered questions about the assigned preparation materials, connected the assigned materials to previous classes and the learning objectives of the class, and generated three to five questions that the preparation materials sparked. Students also had space to report on their progress and share any private questions or concerns. Students also had time at the beginning and end of each class to engage in reflective writing in some form whether as a KWL chart or a topical summary. For example, at the end of each class, students had the opportunity to participate in an anonymous reflection about their experience, in an activity called "Clear as Mud." Students could provide their name if they wanted a personal follow-up from the instructors. We found that students often used this time to share their questions, concerns, and applications around AI and HRM.

AI Demonstrations

In addition to the specific analysis assignments, students were given the opportunity to practice using ChatGPT in the HRM context with specific exercises during class each week. These exercises lasted between 15–20 minutes with the first half being student practice and the second half being an instructor demonstration of how to move beyond the basic outline of the task (see appendix for sample demonstration brief). For example, in Weeks 8 & 10, students were asked to practice engaging ChatGPT to generate parts of an employee handbook for Sunnyside, the simulated organization. After students had a chance to try different techniques, the instructor demonstrated one potential way to accomplish the activity. The instructor then highlighted how to leverage ChatGPT's capability beyond generating written text, including creating a short visual summary of the policy to display on bulletin boards, summarizing the changes between an old and new policy, and highlighting potential conflicts to monitor where the policy may generate inequitable conditions within the workplace.

Instructor use

To support student learning, the instructors also experimented with ChatGPT as part of their work process. The technology was used to generate content and materials for the weekly simulation. A prompt was entered into ChatGPT based on desired learning goals and a generic real-life scenario experienced by one of the instructors. The content generated by ChatGPT was then edited to better suit the needs and capabilities of the students in the class and implemented during the simulation. In the first semester, after the first week of the simulation, we identified that students were struggling to analyze the output of AI (in terms of the generated content) to determine what was most important within the situational context. Some students also struggled to analyze how they could potentially use the tool to support their work as public servants. Part of this struggle was most likely due to the newness of the technology. However, we found that students, just like the instructors, had questions about the flaws in the technology and sometimes were overwhelmed in trying to contextualize how AI could work for them. As a result of this struggle, we developed the weekly demonstrations, which morphed from instructors demonstrating to students first trying and then instructors showing how to navigate the software and analyze the results.

The emphasis of these demonstrations was two-fold. First, we used the demonstrations to help students begin to identify the pitfalls of relying on a strong tool. We found that many students assumed the content was good enough since it was generated by AI. During the weekly demonstration, after the simulation, students and the instructor(s) modeled how to use ChatGPT to generate the simulation materials and critique the output together (as shared above). As part of our class discussion, students spent time reflecting on the challenges of using AI, from the basic questions about bias and privacy to deeper questions. We spent time discussing how while ChatGPT, and other AI tools, can be leveraged to solve problems and increase efficiency and performance, users must know (a) what questions to ask before engaging with the technology, (b) what prompts will provide the best output for the situation, (c) how to evaluate the output, and (d) how to balance ethical considerations when engaging with an evolving tool.

Second, we sought to provide an opportunity for students to see the wide range of uses AI can have within the HRM field. As Afzal et al. (2023) explain, the main elements of HRM including recruitment, training, performance evaluation, etc. are strongly impacted by AI tools. Yet, recent surveys by the Society for Human Resource Management report that practitioners are concerned about bias in AI and are unsure how to best implement AI in their work (Society for Human Resource Management, 2022a, 2022b). Through our demonstrations, we focused on helping students identify the areas where generative AI may be most useful in their work including reviewing the qualifications of job applicants, creating templates that can be altered and customized for organization-wide training, developing project management plans to support employee development and performance, creating job descriptions, and crafting specific personnel policies. For example, in the demonstration discussed above, we also spent time modeling how to use ChatGPT to generate a performance evaluation plan for a new hire, develop a time-bound project management plan based on the performance evaluation plan that listed key elements (times for check-ins, when to conduct reviews, etc.), and identify implementation supports that are needed (like calendar reminders, etc.). We also explored how ChatGPT identifies evaluation tools and key performance indicators (KPIs) for set professions (in this case, an

emergency room nurse) and how to use ChatGPT as a starting point in monitoring KPIs when strategic goals change.

Discussion

Students reflected on some of the challenges of using ChatGPT. While students found the output was a good launching point to develop a product, they explained they struggled to come up with the correct prompt. As a solution to this challenge, students identified they heavily relied on the theoretical principles to edit ChatGPT's output to produce the required content. For example, in the first analysis assignment using AI, students were given a template on how to conduct interviews and generate material to submit for ChatGPT (like KSAs) with basic instructions. Students found that with this untailed approach, their engagement with ChatGPT required a lot more editing on their end to refine and correct the output. As we reflected with students in class and as students reported in their written reflections, the foundational knowledge of what constitutes a job description was an important tool in analyzing the output of ChatGPT. Students noted the experience of inputting all the information without tailoring the prompt, created a lot of repetitive work.

I learned about how to construct a job posting overall. Although I had seen them online before, I never put much thought into the person creating the description. I wasn't aware of the amount of thought and time that goes into this process. I could also see the overall layout and amount of detail in the posting playing a significant role because it's important to attract the right candidates. I think this assignment created a great opportunity for me to go back and revise my work and see what I could potentially improve on. If I am ever tasked with this in the future, I will have a great deal of foundational knowledge. – Student enrolled in MHA program

If I could redo this assignment, I would probably provide ChatGPT with a more specific outline tailored to what I was looking for, potentially including a bulleted list. I think sometimes ChatGPT can fail to highlight specific information and instead provide somewhat irrelevant information.” Student enrolled in MHA program

However, students felt better prepared to engage with this type of activity in the future. In the next ChatGPT-centered assignments, students demonstrated their learning by generating more detailed and complex prompts, signaling the importance of reflecting on learning through the lens of theory.

In general, AI tends to produce information, rather than knowledge, for students to draw upon, making this traditional education practice of reflection on theoretical knowledge an important exercise for students moving forward to understand their interactions with the technology and the subsequent positive and negative consequences of any generated output. We found it was important to help our students frame their interactions with AI through the lens of theory and learn how to analyze their engagement. During our classes, we found that the students who were most successful in engaging and leveraging ChatGPT as a tool for public service had a stronger understanding of the theoretical principles of HRM and spent time reflecting on their understanding of theory through their weekly reading logs and class participation.

Researchers have identified the importance of building a concrete understanding of theory in student performance (Kuhn & Dean, 2004; M. F. Pang & Ling, 2012; M.-F. Pang & Marton, 2005). As students develop a solid understanding of the theory, they can

develop the appropriate mental models to engage critically with the problem at hand and move beyond the “what” and “how” to the “why” (Larsson, 2017). As we provided students with a theoretical understanding of HRM policies, they could move beyond “what” an HRM policy is and “how” to develop a policy to discuss “why” a particular policy mattered. Then, when tasked with generating a new policy for their organization using ChatGPT (see appendix), students could identify the most important parts of the content created focusing on the connection between the “why” of a policy the “what” and “how” of the content generated.

This metamorphosis was important as we identified that students need to understand several things to be successful in their engagement with ChatGPT and any AI tool. These concepts include: (a) knowing what problem the student was seeking to enlist ChatGPT to help address, (b) what processes went into solving the problem, (c) what the desired output should look like (i.e., did the student want policy text, some potential social media posts detailing their engagement, or a suggested script to help role-play a difficult conversation, etc.), (d) what role ChatGPT was playing in the problem solving process (i.e., creator, consultant, brainstorm partner, etc.), and (e) what prompts would maximize the desired output from ChatGPT.

We found that, as instructors, we need to spend time with students discussing the output and how to identify flaws and refine the material produced, including checking for their assumptions and biases. As the output from ChatGPT is not always duplicative, we talked about the importance of understanding the entire process and created opportunities for students to analyze and edit AI output in two forms: (a) created by another user (through materials used during the simulation) and (b) created by themselves (through the analysis assignments). Students who were able to analyze their engagement through the lens of these concepts had more success editing AI outputs and had better experiences overall with AI in the classroom.

Students needed to be trained to be critical users of a technological tool that can discriminate against the very people the technology is meant to support. This training was an area that, upon reflection, we were not able to cover substantively. While we emphasized the importance of understanding the black box of AI and asked students to be vigilant not to share any information that could be covered by HIPAA or FERPA as part of their work, we didn’t develop any protocols to help students assess both the technologies and the users (i.e., the student’s) bias and assumptions

Recommendations

Through reflection on our experience, we identified some things that either helped us integrate AI into our class or we want to incorporate moving forward, which may be helpful for other public service instructors who want to use AI in other areas of public service education.

Recommendation #1: Help students distinguish between information and knowledge

Students should understand that AI generates information and content, but doesn’t necessarily result in mastery of a subject (i.e., knowledge). Students must first put in the work to understand the theoretical foundations before and while engaging with AI. Having this deep

theoretical background will help students better analyze AI-generated content. The weekly AI demonstrations allowed for discussions around the information provided and the knowledge needed to accurately assess the output.

Recommendation #2: Push students to reflect on their work

Students should be pressed to think about how they use the AI tool, what the process before and after using the tool looked like, and any consequences that come from using AI in the stated task. This reflection can be oral or written, but should be revisited often to help the student identify patterns around their AI use including (a) techniques that lead to success or failure, (b) common errors emerging in the AI output, and (c) common questions surfaced by others when reviewing the AI output. Teaching students to be self-aware and reflective is not only a critical teaching practice, but a practice that can provide insights for organizations looking to develop policies around AI use within their organizational context. In particular, student reflections as part of their AI-related analysis assignments were helpful as we could see individual-level concerns and learning trends that could be addressed in future classes.

Recommendation #3: Have a plan to address any privacy and bias concerns before engaging in the tool

As research has demonstrated, AI struggles with questions about privacy and bias (Ntoutsis et al., 2020; Varona & Suárez, 2022). Students should be aware of the conflicts that can be found when any new technology or practice is adopted. Along with educating students about the murkiness surrounding the explainability of a tool (i.e., how an AI made the decision to generate a specific output), students should also consider questions of ethics, bias, and privacy. While we emphasized the importance of avoiding sharing any private information, particularly information governed by HIPAA and FERPA, we lacked a comprehensive plan to address such concerns throughout the course. Instructors should have a plan to help students protect themselves and the data they are using to engage with the system. The best plans are generated with the class itself and evolve over the semester as new ideas or problems are surfaced. Instructors should teach students how to have transparent practices and dialogs around their use of AI to help engage community members concerned about leveraging a powerful, yet potentially harmful tool.

Recommendation #4: Generate multiple opportunities for students to engage with AI within a variety of settings

Students need multiple experiences to analyze both their interactions with the technology and the outputs from that interaction. Ask students to evaluate AI generate content (either their or someone else's) and to generate content together as a learning experience to provide different pathways toward understanding best practices. Help students understand what opportunities can be best for leveraging the use of AI technologies and when the use of such technologies will cause further harm to the public. Providing AI-generated content within a set context, like our Sunnyside simulation, was helpful for students to learn how to objectively analyze AI-generated output.

Recommendation #5: Provide boundaries for student exploration

Students emphasized how easy it was to get lost in the content creation process and feel overwhelmed by the potential of ChatGPT in HRM. For all activities, students should have a clear understanding of what output may look like (either through a rubric or an example assignment). As students can get overwhelmed by the type of content created, the pace of content creation, and the additional variables (like bias, privacy, explainability, transparency, etc.) that need to be considered when generating AI output, instructions should consider providing a set of instructions that can be referred to throughout the process (see [Appendix A](#) for example). While these instructions may vary based on subject, we found it was more helpful to provide written briefs with a stated task, instead of asking students to explore using a particular style of prompt or follow detailed step-by-step instructions. With these boundaries, students were able to focus on exploring different ways to go about the task, including different prompt approaches, and better evaluate their work.

Conclusion

As public service education continues to evolve, we must prepare our future public servants to understand and harness the power of AI while preventing additional harm to vulnerable communities. While the sample is quite small, the experience across both semesters for all students, regardless of degree program, professional background, or previous experience was consistent. Throughout the semester, students became more aware of the benefits and threats of AI, especially within the context of human resource management. The class experience found that ChatGPT helped with tasks that required some level of creativity (like writing job descriptions) or generating templates (like a project management plan for an employee on a performance improvement plan) were more successful while tasks requiring more analysis and detail (like developing specific policies) necessitated more supervision and involvement of the user. This experience mirrors findings from Dell'acqua et al. (2023), which identified a skills distribution within Chat GPT. Dell'acqua et al. (2023) also suggested that as AI continues to emerge as a workplace tool, employees will find different ways to engage with AI including delegating specific sets of tasks to AI or humans or finding a way to integrate the use of AI within their work.

However, the reality is AI is a tool that is still being explored and poses questions about ethics, bias, and effectiveness. Questions remain about the explainability of AI (i.e., how the technology reaches the provided conclusions and outputs), the transparency of data use, the training models, and more. While these are all questions the authors tried to address as part of their teaching, there simply wasn't enough time to provide a substantive examination of each of these topics. As such, further classes, including an "AI in Public Service" course are in development to offer students a chance to examine this technology more in-depth and allow the HRM course to remain more grounded within the context of field-related practice.

In the future, we suggest the integration of more AI tools, including non-generative AI tools like limited chatbots, to help students seeking to merge theory and practice into their education. Additionally, we encourage educators to consider conducting research within their classrooms to identify best practices in applying different types of AI (traditional and generative) in both HRM and public service as a whole. Regardless of the tools used, students will only benefit from

learning how to manage and approach AI before joining the workforce as AI is a technology that has staying power. Students must be trained to separate the concept of gaining knowledge and usable skills from the easy-to-access information and content generation AIs can provide. If students learn to navigate the application of AI in their work, situated in the public context, they will be better prepared to address the implementation and applications of AI in public service in the future.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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Appendix A

Sample AI analysis assignment

The purpose of this assignment is to draft a policy your chosen organization may need based on your analysis of the policy and your understanding of the future of HRM. You are expected to critically analyze the material and provide a well-written response with references. The analysis should be formatted (including references) according to APA guidelines (12-point font, Times New Roman, double-spaced) and submitted as a Word document to Canvas. Writing should be clear, well-organized, and contain minimal grammatical errors. There are two parts to this assignment: (a) justification of the policy and (b) drafting the policy language.

Part A: Justification of Policy

You should aim to provide a draft between 500 and 600 words (including references). This requirement helps you write with brevity and focus on the details most important to the analysis. There are several aspects you will be expected to examine as part of your draft. *Please note that the prompts below only contain suggested sub-questions. You should be thinking critically about the policy and the major questions that need to be addressed. This requirement means you may be answering questions not listed below.*

- **Explain the needed future policy.**
 - What is the policy?
 - What is the purpose of the policy? What is the problem being addressed?
 - What is the process described by the policy? Who is in charge of implementing the policy? What issues are at stake?
- **Discuss the environmental factors involved in the creation/implementation of the policy.**
 - What factors would influence this policy creation?
 - What factors would influence this policy's implementation?
 - What challenges this policy's existence or implementation?
- **Discuss the policy's implementation in the future.**
 - How could the organization implement the adoption of this policy?
 - What resources are available to assist in the adoption and implementation of this policy?
 - How might the organization address challenges to the implementation of the policy?
 - How might the organization leverage environmental conditions to support this policy?

Part B: Policy Language

To help you draft the policy language, you will be using ChatGPT. You will need to submit the following:

- The prompt you use to prompt the generation of your policy. **Make sure you only use publicly available information to guide the ChatGPT results** (for privacy reasons) *Remember, good policies include information about the policy name, the person responsible for updating/implementing the policy, the purpose of the policy, definitions, the scope of the policy, and a policy statement.*
- The output generated by Chat GPT
- Your edits to the Chat GPT output of policy

Part C: Reflection

Reflect on your experience with this assignment. You must answer the following questions. Your reflection should be at least two (2) paragraphs).

- What did you learn while completing this assignment?
- Reflect on your thinking, learning, and work. What were you most proud of?
- If you could do this assignment over, what would you do differently?
- Were the strategies, skills, and procedures you used effective for this assignment?
- How might you incorporate this type of practice into your work?

Learning Objectives

- Learning Objective 1.1: Identify the components of HRM operations.
- Learning Objective 1.2: Explain the environmental conditions that impact HRM practices.
- Learning Objective 2.1: Explain how an HRM manager implements different HRM methods and functions (including, but not limited to job analysis, recruitment and selection, performance evaluation, compensation, training, etc.) to build healthy workplaces.
- Learning Objective 2.2: Evaluate the factors (individual, team, organizational, and environmental) that influence healthy workplace behaviors.
- Learning Objective 2.4: Appraise the need for and best practices related to workplace belonging and inclusion efforts.
- Learning Objective 2.5: Determine the effectiveness of a real-world organization's HRM methods and functions.
- Learning Objective 3.1: Apply their understanding of HRM practices and operations to the public service context.
- Learning Objective 3.2: Identify the relationship between HRM operational requirements, public policy, and social equity.

Sample AI demonstration activity

Instructions

- (1) Open ChatGPT: <https://chat.openai.com/>
- (2) Develop a prompt that produces an onboarding plan for the newly hired CEO that covers some of the concepts we have discussed so far in class: strategic planning, workplace and succession planning, etc.
- (3) Work with the AI to refine the onboarding plan and address the following needs:
 - (a) Address the critical needs identified in the needs narrative found on Canvas
 - (b) Identify the role of the board members and HRM director in the on-boarding process
 - (c) Identify what an effective training would look like
- (4) Edit the product to focus on supporting the onboarding instructions to support a first-time CEO.
- (5) Explore the different supporting products for the onboarding process the AI can generate. Some ideas include:
 - (a) Slide outlines for different training elements
 - (b) Orientation packet materials
 - (c) Reflection questions
 - (d) Calendar of trainings that need to occur throughout the first 90 days, etc.

Learning Objectives





- Learning Objective 2.2: Evaluate the factors (individual, team, organizational, and environmental) that influence healthy workplace behaviors.
- Learning Objective 3.1: Apply their understanding of HRM practices and operations to the public service context.

ARTICLES FOR FACULTY MEMBERS

CLIMATE CHANGE AND SEA TURTLE NESTING

Title/Author	Leveraging neuroleadership and adopting AI to improve human capital development in IT&C business organisations / Staneiu, R.-M., Stratone, M.-E., Dabija, D.-C., & Mititean, P.
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LEVERAGING NEUROLEADERSHIP AND ADOPTING AI TO IMPROVE HUMAN CAPITAL DEVELOPMENT IN IT&C BUSINESS ORGANISATIONS

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Abstract

This paper aims to explore how business organisations in the Romanian IT&C sector strategically implement neuro-leadership principles to accelerate the adoption and implementation of artificial intelligence (AI) technologies, thus enhancing human capital development and promoting sustainable competitive advantages. Applying the focus group method, dynamic discussions were held with 10 representatives of Romanian IT&C companies to highlight how these business organisations strategically implement neuro-leadership principles and adopt AI technologies in human capital management. The results of the research, divided into four main themes, reveal the importance of neuroleadership in improving employee competencies as well as overcoming the challenges associated with implementing AI in organisations. Research provides new and relevant insights for leaders in business organisations to effectively adapt to the complexity of technological change caused by AI adoption in human resource management. At the same time, the results reveal the importance of fostering a culture of continuous learning and development to harness the potential benefits of AI, while mitigating the risks associated with this approach. The originality of the paper is derived from the merging of the fields of leadership, neuroscience, and AI, thus providing a comprehensive understanding of the dynamics shaping organisational responses to technological innovation. The research addresses a notable gap in

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the literature by exploring concrete strategies to accelerate AI adoption through neuroleadership principles, enriching the literature on this multidimensional relationship.

Keywords: neuro-leadership, neuro-leaders, human capital, artificial intelligence (AI), artificial intelligence technologies, employees, and business organisations

JEL Classification: O32, J24, D83, D84.

Introduction

In a society undergoing constant transformation and change, driven by the rapid evolution of technology, AI is emerging as an essential element in the digitisation process, reshaping traditional practices (Allioui and Mourdi, 2023). AI has become an important source of innovation in organisational performance and adaptation of business models, bringing human capital development to the forefront to support such transformation in technically orientated organisations operating in the IT&C sector. AI will fundamentally change the way organisations work and their expectations of employee skills, often compared to the fourth Industrial Revolution (McKinsey, 2022).

Management and leadership practice are seen as important factors in the implementation of AI in business organisations: the confidence that management shows in AI, in conjunction with how they translate it into the company, is fundamental to the adoption of these technologies (Barton et al., 2022). Organisations therefore need neuroleaders who can be agents of change, who can provide clarity to employees in the face of AI-generated uncertainty, who consider human behaviour and the natural reaction of employees to technological developments that fundamentally transform the organisation. The integration of neuroscience concepts into traditional leadership practices, known as neuroleadership, combines knowledge from psychology and elements of human brain anatomy to enable neuroleaders to develop effective strategies and approaches to managing AI within organisations (Pittman, 2020).

Even though leadership theory and AI adoption are widely debated and researched topics, there is an absence of research investigating the integration of neuro-leadership principles in the implementation of AI in business organisations to develop and strengthen human capital. Recent literature addresses the importance of management and leadership practices in AI implementation in business organisations (Nguyen et al., 2022), but does not address concrete ways in which neuro-leadership principles can be strategically leveraged to accelerate the adoption and implementation of AI in business organisations, supporting human capital development.

Therefore, this paper aims to explore how business organisations strategically implement neuroleadership principles to accelerate the adoption and implementation of AI technologies in human resource management, promoting innovation and generating competitive advantage. The research problem is translated into practice using a qualitative methodology, which is based on the focus group method. It was carried out among different representatives from the Romanian IT&C sector.

The paper adds value to the literature by proposing a new perspective on how neuro-leadership can be integrated into the business strategies of organisations implementing AI

in the management of their human capital. Focusing on the technical elements of AI adoption, the research extends studies focused on intellectual capital theory, pointing to the essential role of neuro-leadership and managerial skills in managing the organisational change process (Andronie et al., 2021; Dijmărescu et al., 2022) and the relevance of AI acceptance by employees. By investigating the connection between neuro-leadership and AI adoption, the paper makes a significant contribution to our understanding of how human factors influence the successful implementation of this technology and support an organisational culture oriented towards continuous learning and development of employee competencies.

In terms of structure, the paper begins with a section devoted to reviewing the current state of the literature on key concepts, followed by a section detailing the research methodology. The results section then brings to the fore a critical analysis of the focus group discussions, divided into four thematic categories. The discussions interweave the approach and connect the results of the paper with other previous findings and conclusions in the literature. The paper concludes with a conclusion section, outlining theoretical contributions and managerial implications, along with limitations and future research directions.

1. Review of the scientific literature

1.1 Human capital theory

Investing in human capital is essential for increasing the competitiveness of business organisations, but also for improving the living standards of citizens (Cabrilo and Kianto, 2023). Intellectual capital encompasses the beliefs, attitudes, and actions of the employees of a business organisation, as well as those in leadership positions, which together synergistically contribute to achieving the greatest potential for intellectual development (Quintero-Quintero et al., 2021). Of course, intellectual capital is closely related to human capital, which refers to the traits, skills, and knowledge of individuals that can be developed over time and that together contribute to supporting the growth of the business organisation (Amayew et al., 2019). Closely related to intellectual capital is the training, evaluation, development, recruitment, and motivation of employees. These processes need to be carried out in such a way that they ensure added value for the business organisation (Vătămănescu et al., 2023). Employees of business organisations must possess the ability to learn, innovate, think creatively, and contribute to organisational change; thus, they become a vital source of innovation and renewal of the company's strategy (Quintero-Quintero et al., 2021), which is essential in achieving sustainable market success and generating competitive advantage (Cawthorpe, 2023).

The direction followed by the development of human capital theory goes beyond traditional workforce management and moves toward new strategies to strengthen and develop the potential of everyone within the business ecosystem (Todericiu, 2021). The performance and productivity of an organisation is improved through the effective management of intellectual capital, which includes the skills, experiences, relationships, processes, inventions, and ideas of the employees of the business organisation and the impact of these vectors on the community (Ausat et al., 2022). Careful management of human (intellectual) capital at different organisational levels has produced a richer understanding of the complex dynamics of the business organisation by facilitating and accelerating learning dynamics,

identifying performance-generating practices, and disseminating them within the organisation (Quintero-Quintero et al., 2021). At the same time, business organisations are aided to achieve higher performance through continuous monitoring of human resource development and their intellectual growth strategies. This involves identifying factors that contribute to organisational change and promoting innovation, particularly within economic entities (Hashim et al., 2015; Iwata and Hoskins, 2020), but also in other fields such as art and sports (Byrnes, 2022; Ciocan and Milon, 2017; Byrnes, 2022). Other authors (Dokthaisong, 2021; Rzepka and Witkowski, 2023) warn that as AI becomes increasingly prevalent within organisations, there will be a need to redefine effective leadership by integrating emotional intelligence in order to complement AI-based decisions, and thus ensure effective human capital management.

1.2. Application of neuro-leadership principles in the context of human capital development in business organisations

In addressing organisational dynamics and effectiveness, the interdependence between human capital and leadership plays a key role (Ismail et al., 2023). This relationship is based on an understanding of the complex interaction between acquired skills, know-how, and competencies of the workforce, that is, the leadership techniques that direct and coordinate human resources (Gheerawo et al., 2021; Trifan et al., 2022). From a neuroscientific perspective, researchers are exploring ways to influence human brain responses so that company employees can better contribute to the achievement of organisational goals, be inspired or motivated to perform tasks, and be encouraged to take responsibility (Rodrigues et al., 2023). This delineates the concept of neuroleadership, which is a multidisciplinary field and combines neuroscience and leadership (Cleotenberg and Waslany, 2023).

The literature (Tomlinson, 2021) also addresses the concept of neuroplasticity, which highlights the human brain's capacity to adapt to change. Neuroplasticity constitutes a key factor in leadership, representing the brain's ability to learn new things from the environment (Swingle, 2018). Leaders of business organisations that use neuroplasticity, that is, applying neuroleadership concepts in the management of their companies, can help their employees to become more effective in performing their tasks, to acquire the skills they need more deeply and even faster, that is, to adapt faster to challenges and/or responsibilities (Gheerawo et al., 2021). Leaders of such organisations contribute to the continuous improvement of their employees and promote a culture of change (Sivalingam et al., 2017).

Neuroleadership relies to a great extent on the emotional intelligence of the subjects (Ruiz-Rodríguez et al., 2023). Influencing them and determining them to emphasise a certain behaviour depends to a great extent on the ability of leaders in a business organisation to understand the neurological mechanisms that generate emotional regulation and foster empathy by exploring neuroscientific findings. This understanding becomes crucial to developing the kind of interpersonal connections necessary to maintain productive leadership, i.e., to ensure positive dynamics among business organisation employees, especially in small and medium enterprises (Ruiz-Rodríguez et al., 2023).

Understanding the neurological underpinnings of leadership facilitates the delineation of the neuroscience of social behaviour, as it helps to boost the participation, motivation, and

performance of business organisation employees (Gkintoni et al., 2022). Leaders of business organisations who exhibit neuroleadership skills have the ability to get their staff to collaborate and communicate effectively, control their emotions, and find the motivation to contribute effectively to the achievement of organisational goals, i.e., in the rapid, rigorous, and efficient execution of their tasks. By understanding the fundamental processes of the human brain from the perspective of leadership implications and decision making (Nuez et al., 2023), business organisations can facilitate human capital development through the application of neuroleadership (Rodrigues et al., 2023). AI will become the backbone of organisations' competitive advantage through strategic and operational decision-making capabilities (Torre et al., 2019).

1.3. Synergies between Neuro-leadership and AI in human capital management of the Business Organisation

The attention paid in the literature to the implications and especially the applications of AI in business organisations has skyrocketed in recent years, and it is considered a new industrial revolution (Badghish and Soomro, 2024). The implementation of AI-based technologies in business organisations and their processes enables companies to improve their performance. Compared to other information technologies, AI-based technology includes systems capable of learning, adapting, and connecting very quickly to any change, providing significant benefits to business organisations, such as the ability to anticipate market turbulence in a timely manner, identify market opportunities, and extract the most relevant information from existing data (Wei and Pardo, 2022).

AI is radically transforming the way business organisations hire, manage, and interact with staff. By adopting AI-based technologies, these business organisations can improve their hiring procedures, can more accurately assess employee performance, provide employees with real-time feedback on task performance, thus contributing to continuous improvement in employee performance (Cawthorpe, 2023), and increase staff work productivity (Chowdhury et al., 2023). AI combined with the organisation's employees forms a collective intelligence that facilitates teamwork, creativity, and the rapid making of the most appropriate decisions, leading to innovation and improvement in task performance and administrative activities (Malone, 2019). Due to the increased efficiency of tasks performed by machines compared to manual work, the integration of AI-based systems into the human resources framework of the business organisation allows for better and efficient human capital management (Lim et al., 2019), while they become more flexible and adaptable to changes (Chamorro-Premuzic et al., 2017).

Neuroleadership has a major impact in business organisations, being able to improve decision-making, to streamline the emotional regulation of those involved, and to contribute to the identification of the most appropriate solutions to the challenges and problems encountered. At the same time, neuroleadership facilitates collaboration between management and employees and makes it easier for the business organisation to adapt quickly to change when necessary (Gkintoni, 2022). Neuro-leadership can interact excellently with AI, as its combination provides business organisations with new insights into human behaviour (Roman et al., 2022) and employee motivation and performance, respectively (Lim et al., 2019). Today, business organisations have the ability and

opportunity to maximise their human capital development efforts by embracing and applying the principles of neuroleadership and incorporating AI into the conduct of work tasks and daily activities, respectively (Tiwari et al., 2021).

Combining the fundamentals of neuroleadership with AI in the context of human capital development provides crucial insight and allows business organisations to reconsider their approach and perspectives on reporting to employees (Qin et al., 2023). The integration of AI with neuroleadership enables the enhancement of business organisation effectiveness, as employees can receive real-time feedback on the performance of tasks and work carried out based on preset indicators. Obtaining this feedback helps employees reach their full potential and significantly improve their skills (Khoruzhy et al., 2023).

By adopting the principles of neuroleadership combined with the use of AI, business organisations can improve their ability to recognise, develop, and engage employees in the most effective way possible in their daily tasks and activities. Furthermore, it allows complex and difficult tasks to be assigned according to the competencies and skills, that is, prior knowledge and individual performance of employees (Johannessen, 2020), which implicitly contributes to streamlining processes within companies and increasing their performance. In fact, business organisations can thus significantly improve their productivity, being able to efficiently manage tasks and day-to-day operations by incorporating AI technology into intraorganisational procedures, i.e., human resource management (Roman et al., 2022; Khoruzhy et al., 2023; Qin et al., 2023).

AI has a substantial impact on the HR department, which is vital for the success of the business organisation, as it can help through the adoption of AI-based technologies, the proper recruitment of the workforce, and the identification of the best talent (Kshetri, 2021) or can contribute to a more accurate and rapid evaluation of employee performance (Tian, 2020). AI-based technologies help neuroleaders minimise bureaucracy and recruiters to select the most suitable candidates according to job requirements or organisational needs, saving time and resources, i.e., increasing the productivity of the department and the whole organisation (Kiran, 2021). In fact, AI-based technologies not only simplify the recruitment process, but also make it more rigorous and objective, and less prone to errors or biases in candidate selection (Vrontis, 2022). It is the task of neuro-leaders to choose AI tools that allow them to support the development and/or continuous training of human capital, to define or modify objectives specific to the responsibilities, but also to the competences and skills of each employee, along with the individual and continuous monitoring of overall job performance and efficiency in performing tasks, and to generate feedback.

2. Research methodology

2.1 Research objectives and topics

The purpose of this research is to explore how business organisations in the Romanian IT&C sector strategically implement neuroleadership principles to accelerate the adoption and implementation of AI technologies in human resource management, thus contributing to the development and strengthening of human capital. Through this strategic approach, the increase in organisational performance is considered, as well as the effective use of innovation in the generation of competitive advantages. In this regard, the research is based on the following objectives:

1. Analysis of the concept of neuroleadership and its implications on the development of human capital within business organisations in the IT&C sector by exploring the leaders' perceptions of these entities. This objective was transposed into topics 1 and 2 of the research, which facilitated the exploration of participants' perceptions of the evolving leadership role and the synergies between neuro-leadership and AI technologies used within the organisations under analysis.
2. Examining the processes and procedures required within business organisations in the IT&C sector in the effective adoption of AI in human resource management, objective transposed into research topic 3.
3. Assessing how the integration of AI technologies and tools influences human capital development within business organisations in the IT&C sector, objective transposed into research topic 4.

Thus, the four research themes that facilitated the dynamic exchange of ideas, opinions, and perspectives from the participants are:

Topic 1: Understanding the concept of neuro-leadership and human capital development in business organisations in the IT&C sector in Romania. This theme aims to highlight the importance of applying the principles of neuroleadership in the development of human capital in business organisations to better respond to current market challenges and to allow them to rapidly adapt to change, considering maintaining or increasing employee satisfaction (Ruiz-Rodriguez et al., 2023; Guarnier & Chimenti, 2024). In fact, business leaders must understand the implications of integrating these principles to properly manage and improve human capital development.

Topic 2: The general attitude of the respondents towards the synergies assumed by the implementation of neuro-leadership principles in human resources management within business organisations in the IT&C sector in Romania by applying AI-driven technologies. This theme highlights the connection between the application of neuro-leadership practices and the adoption of AI in business organisations in the IT&C sector in Romania, focussing on how neuro-leaders can support, through their competencies, employees, and teams in performing their tasks and in adapting to change (Badenhorst, 2015; Grunwald, 2021). Certainly, the use of AI-driven technologies enables the development of various necessary competencies for employees to accomplish their tasks in organisations. Neuroleadership must contribute to reducing employee resistance to using AI-driven technologies, especially given the fact that these technologies can improve efficiency, thereby fostering competition to elevate the performance of the business organisation.

Topic 3: Criteria to evaluate the degree of readiness of business organisations in the IT&C sector in Romania for the adoption of AI-driven technologies in human resources management. This topic focusses on assessing the vectors (processes, procedures, tasks, and activities) that a business organisation needs to consider in the successful integration and adoption of AI-based technologies, which are capable of enabling human capital to use them to improve organisational performance. Of course, this analysis implies examining organisational processes and procedures capable of determining whether the company is mature enough to embrace change and manage the risks associated with the adoption of AI. The smaller and more innovative business organisations are in adopting AI, the less resistant they are to change because they are more agile and able to make decisions quickly (Hradecky et al., 2022).

Topic 4: The importance perceived by the participants regarding the impact of the use of AI-driven technologies in the development of human capital within business organisations in the IT&C sector in Romania. This theme aims to outline how respondents perceive the benefits and competitive advantages that AI-based technologies can generate for human capital development within business organisations (Krakowski et al., 2023), in order to improve employee learning processes. At the same time, the aim was to highlight the role of neuro-leadership in overcoming the obstacles, potential risks, and disadvantages associated with implementing AI within these organisations. Thus, this theme aims to showcase the negative aspects of AI adoption in business organisations, such as those caused by cyber security threats or ethical issues arising from insufficient legislative regulations (Bhatt and Muduli, 2022).

2.2. Research design

In transposing the research scope, a qualitative study was conducted through a focus group among representatives of business organisations in the IT&C sector in Romania that apply the principles of neuro-leadership. Resorting to focus group-based research is considered appropriate for analysing topics with a high degree of novelty, but also those based on social components (Nyumba et al., 2018). By involving participants in structured discussions, focus groups allow the exploration of different perspectives on the topic addressed in an interactive way, encouraging all participants to share their knowledge and their own beliefs about the proposed topic through dynamic and informative discussions (Smithson, 2007).

The focus group consisting of representatives of business organisations in the IT&C sector in Romania that apply the principles of neuroleadership was organised in February 2024. It was attended by 10 representatives (see Table no. 1), a number considered adequate and relevant for such an approach (Cortini et al., 2019). The research participants come from different organisations in the IT&C (software development) industry. The organisations are at least 9 years old in the market and have an annual turnover of more than 10 million euros. Their focus is on providing software development and consulting services to a portfolio of more than 120 clients both in Romania and in EU countries. The companies have more than 100 employees.

Table no. 1. Information about the focus group participants

Name	Role	Experience in business organisations	Age	Gender
A.P.	Talent and Recruitment Director	7	35	Female
E.F.	People & Culture Director	5	25	Female
S.G.	People & Culture Specialist	2	23	Female
O.A.	HR Manager	10	40	Female
R.S.	Customers Director	8	27	Male
A.I.	HR Manager	4	32	Female
L.P.	HR Manager	4	30	Female
A.B.	Project manager	6	28	Female
A.T.	Project Manager	2	31	Male
S.I.	Project Manager	3	27	Male

Inclusion and exclusion criteria were used in the selection of the focus group participants. Thus, the inclusion criteria for participants are: 1. higher education; 2. The organisations to which they belong have at least 50 employees; 3. the participants have at least three employees; 4. current/previous experience in leadership positions; 5. international experience; 6. the participants' interest in new leadership practices, organisational psychology, and/or neuroscience. At the same time, certain exclusion criteria were used to exclude participants, namely: 1. not having participated in similar research in the last 6 months; 2. the existence of any conflict of interest with the research team (relatives/relatives); 3. lack of consent to participate in the research.

The focus group lasted 60 minutes and was conducted online, in Romanian, using the Microsoft Teams platform. The questions asked in the focus group were not previously distributed to the participants. The debate was recorded using the Record function in the MS Teams application. The authors transcribed the ideas mentioned by each participant during the debate. Consent to participate in the research, i.e., to record the discussions, was obtained from all participants beforehand. At the same time, the authors informed the participants about the purpose of the research and the methodology, i.e. the process of information collection and processing. Personal data such as their role in organisations, years of experience, age, etc. were collected with their consent. In order to ensure the confidentiality of the information, personal data were anonymised.

The focus group discussions were subsequently translated into English, as due to the research topic, the participants used English terminology quite frequently, which they know from their professional work. Concepts from leadership, psychology, and neuroscience are often taken up in English due to their prevalence in the literature and international business practices. Once transcribed, the data was subsequently subjected to content analysis.

3. Research results

Topic 1. Although neuroleadership has an inherent element of novelty, being a concept that is not yet present in the life of business organisations, participants shared several valuable insights into their perception of the concept and its relationship with, or contribution to, human capital development. Following the discussion, participants reached a consensus that neuro-leadership involves understanding how the human brain works, highlighting skills such as emotional intelligence.

“Neuro-leadership is a type of leadership that focusses on how the brain works and is more connected to people” (Female, 32).

“Neuroleadership helps form more well-rounded, healthier teams that allow an understanding of human behaviour and how it works” (Male, 27).

This perception suggests a natural transition to an innovative leadership approach, based on the principles of traditional workforce management in organisations, but relying heavily on empathy, authenticity, and the creation of a psychologically safe working environment. Participants recognise the potential of neuroleadership to help support and encourage

healthy team dynamics, improve the work environment, and encourage organisational performance by adopting a positive attitude to change.

“More authenticity leads to better performing teams” (Female, 35).

“Neuroleadership helps employees successfully overcome changes and challenges within the team and achieve the task” (Male, 31).

“Through neuroleadership organisations can provide employees with a more flexible and engaging work environment” (Female, 40).

The focus group went on to highlight the connection between neuro-leadership and human capital development in business organisations. Participants perceive neuroleadership as an ally that, once used, facilitates the unlocking of human potential within organisations, as neuroleaders better understand employees and can better connect with those they work with. At the same time, the strategic impact that neuro-leadership can generate in a business organisation was also highlighted, as it is the driver for the adoption of organisational change, by promoting adaptability to market development and/or unforeseen tasks, i.e. it can contribute to a better management of the increasingly complex activities that organisations face in today's turbulent environment. The responses underline the potential of neuro-leadership to manage work teams well, but also to shape character and to foster the development of human capital within organisations, preparing them to better adapt and cope with change.

“Human capital has the opportunity to be better prepared in the face of modern challenges and the high level of uncertainty caused by frequent market changes” (Woman, 25).

“Neuro-leadership can ensure a greater sense of responsibility within teams, it is coupled with leaders' confidence in their people and in reducing stress caused by increasingly complex tasks” (Female, 23).

Looking at the barriers, potential risks, and drawbacks associated with implementing AI-based technologies for human capital development, and the role of neuroleaders in mitigating these challenges, research participants had mixed views. While some identified data privacy or the potential for error in making decisions based solely on algorithmic calculations as obstacles to this approach, others brought up the social component, such as resistance to change or the fear felt by coworkers that the employee of the future might be replaced more quickly by AI. A big concern is that the adoption of AI in organisations will lead to a decrease in human interaction, and neuroleaders will have to work harder to reconnect people and maintain a sense of cooperation and collaboration.

“Humans rely too much on AI to generate things instead of creating, and too much AI will surely lead to hiding or even blocking the feelings behind human actions” (Female, 28).

Topic 2. Discussing the connection between neuroleadership and AI, participants revealed a wide range of opinions and perceptions toward the key competencies they associate with neuroleadership. In particular, they referred to the role of AI in facilitating and developing

these skills and agreed that emotional intelligence is emerging as a fundamental skill, along with conversational intelligence, active listening, and effective communication. During the discussions, participants stressed the importance of emotional regulation as an essential skill for neuroleaders and concluded that managing one's own emotions is essential before understanding the emotions of others. Participants were able to identify what the core competencies of neuroleaders should be: curiosity, innovation, and adaptability, considering that a successful neuroleader should have “curiosity and be innovative” (Female, 28), respectively, be “curious and kind to the team” (Female, 35). The majority of participants felt that it was important for neuroleaders to be drivers of change in business organisations and highlighted the ability of AI to help them by providing them with relevant data quickly and efficiently, as well as acting as a conversation partner able to foster cognitive flexibility and a mindset geared towards supporting the development of the organisation.

“Being a neuro-leader in your own organisation means being a change agent and having a growth mindset (development) and a high degree of cognitive flexibility” (Female, 40).

Using AI technologies, organisations can provide neuro-leaders with resources and tools to continuously refine and/or develop their skills, help them support learning among employees, and advise them in adapting to environmental changes and challenges. In fact, AI can improve leadership practices in the organisation through analytical and critical support.

“Talking to an AI-programmed robot is a great way to understand how you can approach different situations or even simulate a future conversation you are going to have with employees, which helps you look at it from multiple perspectives and scenarios” (Male, 27).

Participants also pointed out the limitations of using AI-based technologies to address the emotional aspects of leadership, as it involves the use of large volumes of data that do not include empathy and/or human intuition algorithms. However, participants believe that AI-based technologies can be used because they can generate new creative ideas, simplifying and streamlining the decision-making process by grounding them in historical data and facts.

“AI in the business organisation will help to improve strategies and identify better approaches, but it will lack the emotional side because AI is based only on data and facts” (Male, 31).
“AI can help decision-making from a data-driven perspective, but it does not take into account human emotion” (Female, 27).

Even though the synergies between neuroleadership and AI are increasingly evident, one point remains unwavering: emotion is a sine-qua non condition of human nature that, for the moment, is not replicated by AI.

Topic 3. Participants almost unanimously stress the importance of having processes and procedures in place within business organisations to enable human capital to reap the benefits of using AI-based technologies. By their very nature, business organisations are

subject to failure if they do not have such internal regulations, as organisational chaos can set in relatively quickly, especially as employees do not necessarily work in an organised way and lose efficiency if they do not have appropriate models of best practice in place, i.e. if they do not have adequate experience to adapt to new situations. Participants identify various key areas where such internal rules should be established and documented, including key competencies, learning and/or training, performance management, providing feedback, ensuring quality management, or even making various forecasts.

“The use of AI-based technologies in relation to company employees should be based on a quality management system in which the roles of each party are clearly defined, but also performance management and different learning procedures” (Woman, 35).
“It is very important that everyone knows what they have to do in order to understand their role in the AI adoption process and how they can contribute” (Female, 40).

Clearly, defining the roles and responsibilities of employees is an essential component in integrating AI-based technologies within business organisations to maximise their impact and benefits on human capital development. The existing regulation within business organisations on how neuroleaders should use data obtained using AI-based technologies was an important focus of the focus group. The participants felt that each company should define its own legal framework, as well as the applicability and limits of the use of data obtained in this way. Of course, this would include the establishment of protocols for data management, current data protection agreements, and the use of data based on ethical principles.

“Organisations should establish clear processes and procedures for managing AI-generated data about their employees” (Male, 27).
“The use of data obtained from employees through AI-based technologies should be regulated through ethical guidelines, as most are in the early stages of discovering the benefits and use of AI and often ethical principles are not followed” (Female, 30).

In the key indicators for assessing the readiness of a business organisation to adopt AI technologies for human resource management, participants considered that it depends on the level of openness of employees to embrace change, the support for such an approach by neuroleaders, which can thus become promoters of change, and the support for the use of AI within the organisation and investment in it to increase business efficiency.

“Adoption of AI-based technologies depends on the number of promoters and the openness of neuro-leaders, who can drive the use of AI within their own companies if they understand its benefits” (Female, 23).
“The use of AI within the company also depends to a large extent on the level of the openness of employees to accept change or how curious they are about it” (Female, 28).

Following the debate, it was concluded that the real adoption of AI-based technologies must consider and start with people: if employees are motivated, engaged, and truly understand how these new technologies can help them automate their repetitive work, then they will be more open to adopt and use such technologies. Continuous learning and fostering a growth-orientated mindset in the organisation they are part of are among the key

competencies of neuro-leadership, so organisations that cultivate and foster these types of leader are more likely to be successful in the marketplace.

“The basis would be to make sure that people in the organisation share this interest in adopting AI and understand its benefits and limitations” (Female, 40).

Topic 4. Participants shared their views on the concrete contexts in which AI can be used in business organisations to support, develop, and/or train human capital. Most participants highlighted the opportunity to create and develop personalised learning initiatives, tailored to their needs and expectations, career development and/or pathways, and individual skill level. Thus, it was felt that ‘AI can be used for personalised learning materials’ (Female, 28), which would facilitate the development of effective learning tools that could be tailored to each employee’s learning style. Business organisations will also be able to see real benefits in the development of employee creativity, as they will have more cognitive space to generate creative and new ideas as a result of some of the repetitive tasks previously carried out being automated using AI technology.

Participants also noted that for human capital development, business organisations could resort to the use of virtual assistants to provide personalised support and guidance to employees during their learning, training, and/or acquisition of different skills in the workplace. However, organisations can fundamentally change the traditional learning process and create a framework in which each employee, through the use of AI, is provided with personalised recommendations for the development of their skills and competencies. In fact, two focus group participants mentioned that they used AI as a virtual assistant, which put them in real-life scenarios and facilitated interactive learning experiences. In this way, the participants simulated difficult situations or discussions they were about to face in their own organisation, and the AI-based technology helped them, by simulating different specific contexts and by dialoguing on some concrete situations, to be more prepared for real situations.

Participants also explored ways in which the use of artificial intelligence in developing and/or improving human capital can help business organisations gain new competitive advantages. They highlighted the potential to increase the profitability of companies by adopting AI-based technologies in human capital development and highlighted the impressive ability of these technologies to help improve operations, saving time and enabling better work productivity and shaping employee creativity.

“AI used to manage employees in the organisation saves time and reduces costs and the business is more profitable” (Female, 40).

“An AI technology means reduced costs, time efficiency, more accurate deliverables” (Male, 27).

“If AI is used in the management of company employees, it means that employees spend less time on recurring tasks” (Male, 31).

In the adoption and implementation of AI-based technologies for the human capital management of the business organisation, neuro-leaders are seen as essential pillars of this

process, but also of managing the challenges generated by AI, guiding employees towards the acceptance of these technologies. At the same time, neuroleaders are also responsible for empowering employees to embrace change and perceive it as an opportunity for personal development as well as a threat. By fostering a mindset of self-development, neuroleaders encourage the employee, emphasising cognitive flexibility and neuroplasticity, which helps employees to develop new neural connections and better cope with the challenges of performing tasks at work.

“Neuroleaders must be intermediaries between employees and AI, achieving a fusion between emotions and rationality, guiding staff to accept change” (Male, 27).

“Neuroleaders, by being able to understand how human behaviour works, can better manage resistance to change, ensuring a smoother transition to AI practices and tools” (Female, 40).

4. Discussions

AI has the potential to boost an organisation's productivity in various ways, notably by mitigating risks through more accurate predictions, simplifying the adoption of existing technologies, and increasing creativity and innovation (Damioli et al., 2020). In business organisations that have integrated AI, it has been noticeable that the entire structure and hierarchy of the role of human capital has been altered, and they have become more efficient and agile, using fewer procedures. Their operating costs decreased, and employees relatively quickly became more competent (Rony and Yahaya, 2021). If an organisation's staff understands, trusts, and embraces AI, the potential benefits of this interaction are manifold, both for the individual and especially for the organisation. The degree to which advanced AI systems enhance creativity and organisational performance depends primarily on how staff interact with and understand these systems. The level of human capital preparation is an important factor that ensures the smooth integration of AI within the business organisation (Soni, 2023). AI helps organisations to find the best solutions to solve complex problems more efficiently, which increases company productivity and helps them to be more prepared for uncertainty; they become more efficient and agile (Ramachandran et al., 2021).

Neuroleadership is a topic with multiple implications and facets and is still in the early stages of academic research (Psychogios, 2021), especially in terms of its application in business organisations. The literature is extremely scarce in analysing the impact and effects of neuro-leadership in developing and/or enhancing human capital by integrating AI into daily activities carried out in the workplace (Khoruzhy et al., 2023; Qin et al., 2023). From a practical perspective, a neuro-leader must have a transformation-orientated vision, welcome change, provide direction to the team he or she leads, and lead to the transformation of organisations (Trifan et al., 2022). The neuro-leader can help create a work environment where human capital develops easily and quickly. In the Romanian business environment, Teac (2023) introduces neuromanagement as a new opportunity, proposing it as a potential way to explore the intersection between neuro-leadership and human capital development.

Recent literature (Gheerawo et al., 2021; Riva et al., 2021, Tomlinson, 2021) finds that relevant aspects influencing neuroleadership include employee agility, emotional and social intelligence, self-development mindset, as well as performance-orientated attitude, rapid learning and empathy. Business organisations can make the most of their efforts to create human capital by adopting neuroleadership practices and integrating AI into their daily activities (Tiwari et al., 2021).

Conclusions

Society is on the verge of a technological revolution that is set to fundamentally change the way international economic actors, jobs, and the individual-team-organisation triad look. Throughout the evolution of humankind the only constant has been change, individuals are once again forced to adapt in the face of dual innovation: on the one hand, AI represents a significant opportunity for automating repetitive aspects of work, enabling the efficient integration of human-technology interaction; on the other, AI is perceived as a threat to the status quo with potentially destabilising potential for those who are not prepared to adopt and adapt to it.

From a theoretical perspective, the paper extends research focussing on intellectual capital theory, which is addressed in relation to neuroscience and the implementation of AI-based technologies in the workplace. The research results revealed both opportunities and challenges associated with the implementation of AI in the development of human capital in business organisations. While there is significant potential to increase operational efficiency and organisational performance through the use of AI in human resource management, there are associated risks and barriers, such as concerns about the privacy of employee data, resistance to the adoption of these technologies, or paradigm shifts in the workplace. Like any technological innovation, AI is not a zero-sum game, but a complex system that encompasses benefits, risks, and obstacles.

From a managerial perspective, the paper addresses the crucial role played by neuroleaders in addressing the challenges induced by the use of AI-based technologies in human capital management within their own organisations. Neuro-leaders can act as agents of change, guiding employees, teams, and the whole organisation to embrace the changes proposed by AI, helping to combine emotions (the human factor) with rationality (the technological factor). Through conversational intelligence and emotional regulation, neuroleaders can facilitate an optimal transition to AI-driven practices and promote a growth mindset within organisations by cultivating the belief that learning is continuous.

Among the limitations, the generalisability of the results to other industries or other countries to Romania and the IT&C sector can be pinpointed. The sampling and methodology used is another limitation of the research, the small size of the number of participants influencing the representativeness and generalisability of the results.

In terms of future research directions, a deeper exploration of how AI can be integrated into human resource development programmes to enhance human capital development can be foreshadowed. Research could also focus on developing models and tools to assess organisational maturity in adopting AI. Finally, other industries could also be considered to explore the impact of AI and the role of neuroleadership, such as the automotive or energy industries.

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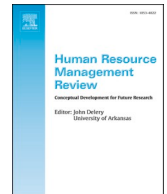
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Unlocking the value of artificial intelligence in human resource management through AI capability framework

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ABSTRACT

Artificial Intelligence (AI) is increasingly adopted within Human Resource management (HRM) due to its potential to create value for consumers, employees, and organisations. However, recent studies have found that organisations are yet to experience the anticipated benefits from AI adoption, despite investing time, effort, and resources. The existing studies in HRM have examined the applications of AI, anticipated benefits, and its impact on human workforce and organisations. The aim of this paper is to systematically review the multi-disciplinary literature stemming from International Business, Information Management, Operations Management, General Management and HRM to provide a comprehensive and objective understanding of the organisational resources required to develop AI capability in HRM. Our findings show that organisations need to look beyond technical resources, and put their emphasis on developing non-technical ones such as human skills and competencies, leadership, team co-ordination, organisational culture and innovation mindset, governance strategy, and AI-employee integration strategies, to benefit from AI adoption. Based on these findings, we contribute five research propositions to advance AI scholarship in HRM. Theoretically, we identify the organisational resources necessary to achieve business benefits by proposing the AI capability framework, integrating resource-based view and knowledge-based view theories. From a practitioner's standpoint, our framework offers a systematic way for the managers to objectively self-assess organisational readiness and develop strategies to adopt and implement AI-enabled practices and processes in HRM.

1. Introduction

The availability of big data and emergence of Internet of Things in the past decade has made Artificial Intelligence (AI) enabled

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technologies top priority for business organisations. AI has become the key source of business model innovation, process transformation, disruption and achieving competitive advantage in organisations embracing data-centric and digital culture (Ransbotham et al., 2020). In this context, existing literature has reported that the adoption of AI has increased by 70% in the last five years (Ghosh, Daugherty, Wilson, & Burden, 2019). International Data Corporation has predicted that the global spending in AI will increase from \$85.3 billion in 2021 to more than \$204 billion in 2025, making the compound annual growth rate 2021-2025 to be 24.5%. According to the predictions made by World Economic Forum adoption of AI will make 75 million jobs redundant and create 133 million new ones worldwide by 2022 (WEF, 2018).

The impact of AI in transforming both businesses and societies is comparable to that of the internet and world wide web, and latter led to the emergence of ecommerce, consume-centric practices, sharing economy and gig economy (Malik, Budhwar, & Srikanth, 2020). The emergence of AI-based systems in the business organisations will significantly transform work force demographics, nature and meaningfulness of jobs, employer-employee relationship, relationship between people and technology, customer experience, and competitive advantage within dynamic market environment (Connolly, Fieseler, Cérne, Giessner, & Wong, 2021; Wilson, Daugherty, & Bianzino, 2017). A study conducted with 8,370 employees, managers and HR leaders across 10 countries that has been reported in Oracle and Future Workplace (2019) found that: (1) 50% of the human workforce are using some form of AI in their workplace in 2019, compared to 32% in 2018; (2) 76 percent of workers (and 81 percent of HR leaders) find it challenging to keep up with the pace of technological changes in the workplace; (3) 64% of people will trust a robot more than their manager. Workers want a simplified experience with AI at work, asking for a better user interface (34 percent), best practice training (30 percent) and an experience that is personalized to their behaviour (30 percent).

Even though AI has been a focal topic for several decades, there is currently no single universally accepted definition throughout the literature, which leads to a fundamental problem of coherent understanding of AI (Mikalef & Gupta, 2021). We have identified and selected eight definitions of AI from multiple disciplines to enable a more comprehensive understanding of AI in the HRM context (see Table 1). These definitions capture the overlap between AI, business analytics, mimicking human like behaviour, i.e., replicating human cognitive processes and emulating human learning mechanisms. Considering the AI conceptualisations presented in Table 1, we define, AI as the ability of a manmade system comprising of algorithms and software programs, to identify, interpret, generate insights, and learn from the data sources to achieve specific predetermined goals and tasks. In line with this definition, our understanding of an AI application (in the HRM context) is that of any form of manmade system comprising of algorithms (derived from computing and mathematics literature), which are translated into software programs. While calling AI as manmade may be debatable (Steels & Brooks, 2018), we are yet to come across an AI system which is developed by AI itself in HRM. The software program has analytical capabilities and computational power to efficiently process big data, generate insights and simultaneously learn from it (Malik et al., 2020). Finally, the tasks and goals are predetermined, i.e., AI algorithms employed have a specific purpose and context to achieve desired outcomes (Kaplan & Haenlein, 2020). For e.g., the algorithms used for analysing sentiments from textual data differ from the ones used for analysing emotions in a static photograph and when compared to emotion detection in live videos. Therefore, the definition primarily covers the two core aspects of this emerging technology: (1) it is manufactured (artificial); (2) it has some form of intelligence (i.e., ability to learn from the data just like human beings learn from their experiences in life).

The existing literature has claimed and outlined several benefits of AI adoption which includes, enhancing business productivity by optimising business operations and resources (Faulds & Raju, 2021), business model transformation/re-engineering (Duan, Edwards, & Dwivedi, 2019), decision-making through predictive intelligence (Paschen, Wilson, & Ferreira, 2020), reducing employee costs and enhancing employee experience, job satisfaction and customer service (Bughin et al., 2018). This has led to increasing uptake of AI-enabled solutions in HRM sub-functional domains such as talent acquisition, video interviews, employee training and development (Maity, 2019), performance evaluation, talent prediction (Upadhyay & Khandelwal, 2018) and employee engagement (Bankins & Formosa, 2020). In this context, recent reviews have outlined the role of AI to facilitate HR analytics (Margherita, 2021), and its potential impact on HRM processes and practices (Vrontis et al., 2021).

Despite the above interest and claims regarding the applications, benefits, and impact of AI in HRM, the existing literature has

Table 1
AI definitions

Citation	Definition
Kaplan & Haenlein, 2020	A system's ability to correctly interpret external data, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation
Van Esch, Black, & Ferolie, 2019	Any intelligent agent (e.g., device) that distinguishes between different environments and can take a course of action (s) to increase the success of achieving predetermined objectives
Malik et al., 2020	AI, in business refers to the development of intelligent machines or computerised systems that can learn, react and perform activities like humans for a range of tasks
Makarius, Mukherjee, Fox, & Fox, 2020	A system's capability to correctly interpret external data, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaption
Schmidt, Biessmann, & Teubner, 2020	The endeavour to mimic cognitive and human capabilities on computers
Wamba-Taguimdje, Wamba, Kamdjoug, & Wanko, 2020	A set of theories and techniques used to create machines capable of simulating intelligence. AI is a general term that involves the use of computer to model intelligent behaviour with minimal human intervention
Mikalef & Gupta, 2021	AI is the ability of a system to identify, interpret, make inferences, and learn from data to achieve predetermined organizational and societal goals
Dwivedi et al., 2021	The increasing capability of machines to perform specific roles and tasks currently performed by humans within the workplace and society in general

found that many companies have failed to experience anticipated benefits (Fountaine, McCarthy, & Saleh, 2019). A survey conducted by Boston Consulting Group and MIT found that the seven out of ten AI projects generated limited impact (business value), and therefore AI implementation plans had dropped from 20% in 2019 to 4% in 2020 (The Economist, 2020; Deloitte, 2017). Research has also found that organisations often find it difficult to integrate AI within their business processes and systems, which inhibits AI adoption (Davenport & Ronanki, 2018; Mikalef, Krogstie, Pappas, & Pavlou, 2020). On one hand the reports from early adopters have indicated that investment in AI is failing to incur business value, while existing literature has outlined the potential of AI to generate business (Ransbotham, Kiron, Gerbert, & Reeves, 2017). While the recent academic reviews in the HRM literature (Margherita, 2021; Vrontis et al., 2021), have focussed on the impact of intelligent automation on firm performance, and facilitating human resource analytics, our study builds on and further extends them by answering the following research question.

What are the key organisational resources required to successfully adopt and implement AI in HRM (i.e., develop AI capability), which will lead to creating business value?

The primary objective of this article is to systematize the academic inputs through a comprehensive and systematic review of literature drawn from multiple disciplines, which includes HRM, international Business (IB), operations management (OM), information management (IM), general management (GM), addressing the recent calls and reviews on AI in HRM (Budhwar & Malik, 2020a; Budhwar & Malik, 2020b; Vrontis et al., 2021). Therefore, we are able to go beyond the boundary of HRM to synthesize and consolidate the current state of knowledge in the context of AI applications and adoption in HRM. In doing so, we theoretically contribute to AI scholarship in HRM, by developing the AI capability framework, consolidating all the technical and non-technical organisational resources that will help to capture the potential value from AI implementation (Mikalef & Gupta, 2021). This framework provides a holistic understanding of resources and strategies necessary to adopt AI within HRM. Second, the framework helps to unearth the importance of complementary organisational resources and not just technical infrastructure to adopt AI and achieve organisationally valued outcomes (e.g., business and employee productivity). Third, our review sheds light on the importance of developing collective intelligence within the organisations, i.e., a collaborative working environment where AI and human intelligence (HI) can co-exist, therefore introducing the new research stream, AI-employee integration, and the role of HRM in this context. Finally, the framework consolidates the multi-disciplinary literature to create a research agenda shaping the direction of future AI research in HRM.

In terms of implications for HRM managers, the proposed capability framework will offer an objective tool to self-assess the organisational resources, which will help to determine the organisational readiness to adopt and implement AI-enabled solutions. The self-assessment will help HRM managers and senior leadership to develop AI strategies clearly focussing on the purpose of using AI, the fit between the desired purpose and AI adoption, anticipated outcomes, and key performance indicators to measure the benefits of AI implementation. This will facilitate developing concrete business cases of AI implementation aligned to solving HRM problems, enhancing HR processes, and therefore serve as a blueprint for other players in the industry. Our review also provides useful insights that will help managers to strategize AI-HI integration within the organisation, to develop collective intelligence capabilities. While this is an unknown territory for HRM practitioners, our initial recommendations will help organisations to enhance understanding, trust, confidence, and satisfaction of employees with regards to AI adoption for developing symbiotic partnership between AI and human workforce,

The rest of this paper is organised as follows: Section 2 will present the review methodology. Section 3 will discuss the findings from the systematic review of literature, which is classified into five different themes. Section 4 will present the AI capability framework summarising the findings of the review and developing linkages between the five discussed in Section 3. The research propositions stemming from the review are presented in Section 5. Finally, we conclude with the research implications and limitations of the review in Section 6.

2. Review methodology

We have conducted a systematic review of literature following the protocol suggested in the existing literature (Hopp, Antons, Kaminski, & Salge, 2018; Tranfield, Denyer, & Smart, 2003) to ensure that the review process is transparent, easily reproducible, and systematises research themes critically.

2.1. Selection of articles

We have used a list of 56 journals in HRM, General Management (GM), International Business (IB), Information Management (IM), which was also adopted by Vrontis et al., 2021 and Cooke, Veen, & Wood, 2017. We have also included Operations Management (OM) journals in our review. We have selected journals from multiple disciplines because the role of AI in HRM has received significant attention these disciplines. We aim to develop links between the works published in these disciplines to make this review comprehensive and add rigor. The final list comprised of 82 journals (ranked 3, 4 and 4* in the on the Association of Business Schools Journal Guide 2020). As the review focussed on AI in HRM, therefore we have included research works overlapping with HRM practices, processes, issues related to AI adoption.

2.2. Search strategy

To establish the search strings, we have identified trends in the keywords usage (AI in HRM) by performing an initial scoping search of relevant articles in two research databases - SCOPUS database and Business Source Ultimate (EBSCO). The search was followed by examining the keywords used in the recent review articles (for e.g., Vrontis et al., 2021; Margherita, 2021), and both empirical and conceptual studies (for e.g., Malik, Tripathi, Kar, & Gupta, 2021; Makarius et al., 2020; Mikalef & Gupta, 2021). For specialised HRM Journals, the search string used was: ("intelligent automation" OR "artificial intelligence" OR "AI" OR "conversational agent" OR "chatbot" OR "bot" OR "machine" OR "machine intelligence" OR "automated intelligence" OR "collective intelligence" OR "collaborative intelligence"). For non-HRM journals, given the diversity of articles and topics covered in the context of AI, we used HRM-related keywords to exclude studies which did not cover HRM issues. The search string used was as follows: ("intelligent automation" OR "artificial intelligence" OR "AI" OR "conversational agent" OR "chatbot" OR "bot" OR "machine" OR "machine intelligence" OR "automated intelligence" OR "collective intelligence" OR "collaborative intelligence") AND ("HR" OR "HRM" OR "human resource management" OR "human resource" OR "IHR" OR "IHRM" OR "international HRM" OR "employ* relation*" OR "human resource development" OR "human resource performance system" OR "human resource analytics" OR "people analytics" OR "talent analytics" OR "workforce analytics" OR "HR analytics" OR "human capital analytics" OR "human collaboration" OR "employee integration" OR "socialisation" OR "teammate"). These keywords were derived from the recent reviews concerning AI in HRM (Margherita, 2021; Vrontis et al., 2021) and prior systematic reviews within the area of HRM (Cooke et al., 2017; De Kock, Lievens, & Born, 2020).

The search was also conducted in individual journal websites, where a journal was not included in the database or the abstract was missing in the final list of articles (for e.g., California Management Review and Harvard Business Review), or the search results did not show the articles from the selected journal list. A filtering mechanism was employed in the research databases to ensure that the metadata extracted is meaningful and aligned to the core research question being investigated. The filtering mechanism used the following inclusion criteria: (1) all types of peer-reviewed journal articles to ensure scientific rigor; (2) articles published in English only (to facilitate natural language text analytics processing); (3) the search string should appear either in the abstract, title or the author listed keywords of the articles; (4) subject areas chosen were business, management, decision sciences, and social sciences; (5) additional keywords which were absent in the search string and related to HRM recommended by the search interface were included

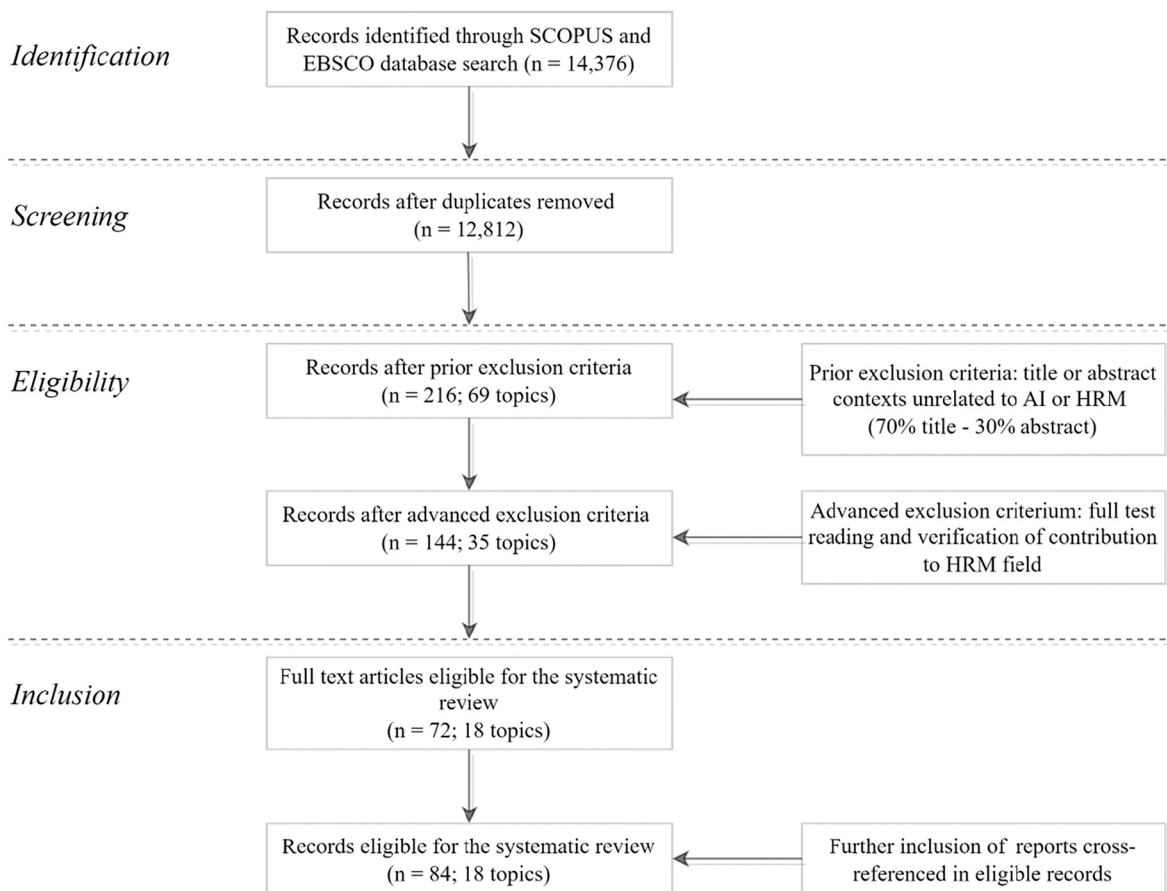


Fig. 1. Selection process for the review

(iteratively); (6) time duration was not restricted to obtain maximum number of relevant articles (last search date: Jun 2021).

2.3. Article screening (See Fig. 1)

After collecting the metadata from all the articles conforming with the search criteria from the SCOPUS database and EBSCO, we used a script written in R open-source programming language to eliminate all the duplicates. Our initial sample of potentially relevant studies was 14,376 articles. After capturing all the metadata for each article, we created a data repository capturing the title and abstract of each article. Given notable advances in natural language processing techniques, we employed a topic modelling, which is a machine learning technique to analyse the text corpus. For this study, we employed a topic modelling algorithm known as Latent Dirichlet Allocation (LDA, Blei, Ng, & Jordan, 2003) technique on the repository. The output of the algorithm is set of keywords representing a topic, and each article is characterized by a particular topic probability distribution (defined as the probability of an article being associated to a topic). This process employs an unsupervised machine learning technique, meaning that it does not require prior categorization (of topics) by the researcher, but rather relies on statistical procedures to identify topics.

The execution of topic modelling on 12,812 articles (after removing duplicates) resulted in 69 topics, and each topic was represented by a set of keywords. Only 35 topics were found relevant to the study, therefore articles belonging to other topics were manually screened and removed, to deal with misclassification errors of the algorithm. Next, we employed a coding process, where each member of the research team gave a meaningful identifier/name for each topic considering the keywords listed under that topic (for 35 topics represented by 216 articles). After the individual coding process, all authors came together to finalise the topics corresponding to each cluster of keywords, and then went on identifying the topics which are relevant to our research question. Based on the above exercise, we found 18 topics relevant to the study (72 articles + 12 from cross-referencing). This was followed by executing another algorithm in R (integrating topic modelling and text mining) to identify manuscripts that were related to these 18 topics. The output was a heatmap and a probability distribution, showing the relevance of the articles to each topic. We found 84 articles relevant to the study matching these 18 topics. Each article was reviewed by the authors to extract meaningful information and store this information in a document extraction table D1 capturing the following data for each article: (1) citation; (2) title and abstract; (3) keywords used by the authors; (4) type of article (review, conceptual, empirical); (5) key contributions of the article; (6) key results and corresponding findings; (7) key limitations and future direction; (8) commentary on the relevance to the topic; (9) relevance to other topics. This process followed the recommendations outlined in (Tranfield et al., 2003) to ensure that the procedure is transparent, reproducible, and devoid of human errors.

Based on the document extraction table D1, we created the following tables in an Excel spreadsheet: (1) list of applications of AI in HRM reported in the literature; (2) list of drivers (for AI adoption in HRM) outlined in the existing research; (3) list of AI adoption barriers discussed in these articles; (4) under-researched themes (formulated from the last columns 7, 8 and 9 in D1). Next, all the tables were verified by each team member to ensure that the information is consistent with the literature and covered all relevant information (e.g., study protocol, or strategic implications relevant to our research question). Next, all the tables were integrated to propose a list of resources required to successfully adopt AI within the organisations, which facilitated the development of the AI capability framework for HRM applications. Finally, our research team used the knowledge extraction document (D1) to find common streams of research between the articles (primarily using column 8 - research topic), and then categorized them into research themes (merged multiple similar topics to form a single theme), which will enable us to answer our research question. This was initially done individually by each researcher and then consensus was reached through a group discussion to finalize the key themes.

3. Findings

We have used topic modelling algorithms and coding conducted by the research team members to find common topics between the articles, and then clustered similar topics together to form research themes, which will: (1) enable us to answer the research question; (2) identify the trending research areas; (3) find the knowledge gaps and inconsistencies; (4) propose research priorities. The key research themes stemming from our review analysis and topic clustering are: (1) Applications of AI in HRM; (2) Collective Intelligence (i.e., AI-human collaboration); (3) AI and employment; (4) Drivers to AI adoption; (5) Barriers to AI adoption. We will discuss the key findings related to each theme, rather than providing an exhaustive analysis of each article, similar to the approach followed in other AI-related systematic reviews in HRM (Margherita, 2021; Vrontis et al., 2021).

3.1. AI applications

The literature on AI has provided several classifications of the technology based on the types of intelligence and corresponding applications of in business organisations (Haenlein and Kaplan, 2019; Daugherty, Wilson and Chowdhury, 2019): (1) automated intelligence (such as digital smart assistants and chatbots) can perform automated rule-based routines (often considered as trivial repetitive tasks) which will free-up time for human workers to spend effort on non-trivial and creative responsibilities; (2) assisted intelligence (such as recommendation systems) can help data-driven decision-making by analysing and deriving insightful knowledge from multiple streams of heterogeneous big data; (3) augmented intelligence (such as speech recognition systems and visual image processing) stemming from machine learning capability of AI algorithms can both assist and augment decision-making agility in any situation; (4) autonomous intelligence (self-driving vehicles, cobots in warehouses, robotic waiters) can adapt to the working environment (leveraging machine learning) without the need of human involvement from an operational perspective (but will require humans to design, develop, govern and manage such systems).

In the field of HRM, AI is seductive as it alludes to an ability to reliably understand and predict human behaviour within an organisation, which in turn, has great appeal for managing productivity. HR analytics is described as a ‘must have’ capability for the HR profession, serves as a tool for creating value from people and a pathway to broadening the strategic influence of the HR functions (CIPD, 2013). Organisations are investing in AI-enabled HR software packages to collate and make sense of the employee data available for achieving strategic organisational goals. Case in point, data stored in cloud platforms like HRIS (HR Information Systems) are composed of information on employee’s demographic information (employment history, skills and competencies, formal educational qualifications and demographic information) alongside softer performance data that might be collected at appraisals and performance reviews (Angrave, Charlwood, Kirkpatrick, Lawrence, & Stuart, 2016). In this context, AI-driven HR analytics has emerged as a popular research area within HRM (Baakeel, 2020), leveraging datasets stored in HRIS. It allows to redefine the way companies will manage their workforce (Giermindl, Strich, Christ, Leicht-Deobald, & Redzepi, 2021), particularly to have a proficient workforce (i.e., suitable skills, expertise and experience) required to succeed in the organizations (Singh & Malhotra, 2020; Sivathanu & Pillai, 2018). The purpose is to leverage the power and potential of state-of-the-art AI-enabled systems to guide decisions. This will allow organisations to develop the capability of workforce, improve teamwork, support flexible working and improve performance measurement (Chornous & Gura, 2020). Recently a review reported by Margherita, 2021 has presented several applications of HR analytics, and offered insights that will help to design AI-based HR analytics projects within the organisations.

AI is valuable in HR decision-making (case in point employees) because of the potential to avoid subjectivity, with more objective decisions guided by the information extracted through employee data mining (Chornous & Gura, 2020). Initially, the role of AI was linked to the development of expert systems for job evaluation (Margherita, 2021), but it can be now linked to activities in the whole HR life cycle. Employee monitoring tools can help identify issues, share insights, guide decisions and encourage stakeholders to act, whereas organizational research helps examine aspects that are relevant for the organization and an evidence-based culture encourages decisions being made based on analytics and data (Peeters, Paauwe, & Van De Voorde, 2020). Sparrow, Cooper, and Hird (2016) cite the example of Tesco analytics tools to understand its customers to better understand its workforce and similarly how McDonalds was able to identify staff demographics, management behaviours and employee attitudes to optimise employee performance. The above examples demonstrate that there needs to be strategic insight among senior HR professionals to direct the use of AI-driven HR analytics within firms. Sparrow et al. (2016) argue that this strategic focus needs to be contextualised within the organisation. The use of technology to support HR has significant potential to support the business strategy (Kakkar & Kaushik, 2019).

AI can be used for various aspects of recruitment. Based on the model proposed by Mehrabad and Brojeny (2007), it can be used to select applicants from a pool of submitted applications (selection), make a decision based on the interview and organisational need (appointment) and propose a suitable salary and benefits based on their qualifications. This is even more so during times of crisis when organisations need to be resilient. AI recruitment has become increasingly more efficient at finding and hiring high quality staff than wholly human centred recruitment (Black & van Esch, 2020). AI recruitment decreases the time taken to recruit individuals, enables organisations to respond to events more quickly and ultimately improve their competitive advantage through intangible assets of better recruited people. Tambe, Cappelli, and Yakubovich (2019) show that the use of AI allows several prediction tasks for recruitment, selection, on-boarding, training, performance management, advancement, retention, and employee benefits. In particular, Baakeel (2020) examined the use of AI in recruitment, and found the potential for fast resume scanning, quickly and automatically responding candidate’s queries, and virtual recruitment activities.

AI has a significant potential to support organizational research because of the capacity to analyze multiple streams of big data and support decision-making. AI can be useful to describe job requirements to attract the best suited candidates (Saling & Do, 2020), to undertake sentiment analysis for monitoring new employees joining the company (Kakkar & Kaushik, 2019) and employee motivation (Saling & Do, 2020), to support hiring decisions through screening and matching profiles with job roles (Peeters et al., 2020), to access a larger pool of candidates and reduce bias eliminating subjective criteria (Kshetri, 2020), to forecast absenteeism (Araujo, Rezende, Guimarães, Araujo, & de Campos Souza, 2019), to improve retention through predictions at the individual level (Kshetri, 2020; Saling & Do, 2020), and to support decision-making for team formation (La Torre, Colapinto, Durosini, & Triberti, 2021). Kot, Hussain, Bilan, Haseeb, and Mihardjo (2021) argue that the appropriate implementation of AI to support recruitment and retention can be essential to enhance employer brand and reputation as well. A list of HRM practices where AI has been used is presented in Appendix 1.

3.2. Collective intelligence

The existing literature has suggested that the superior computational power, big data analytical capabilities and ability to derive meaningful insights from multiple data streams can augment human intelligence by dealing with the complexity in any data-driven decision-making process, rather than completely replacing the human intuitive intelligence from the process (Jarrahi, 2018). The motivation of using AI-based intelligent systems in the context of data-driven decision-making is to enhance the productivity of decision-makers (agile decision-making capabilities) and business organisations through process optimisation by leveraging big data (Wilson & Daugherty, 2018). It is envisaged that AI understanding, trust, and job role clarity will facilitate to create valued outcomes for both the employees and organisations through such a symbiotic partnership which would lead to developing collective intelligence (AI-HI working together) strategies and capabilities within the business processes (Chowdhury et al., 2022). The use of AI was originally seen as benefiting the workforce by providing tools to enhance day to day working tasks. However, this view of AI is now being extended to encompass more than tools to support organisational performance and productivity, but for AI to become more like a peer and fellow teammate. The idea was first discussed by Malone (2018), who considered the intelligence of humans and that of machines as the intertwining of ‘collective’ intelligence. The machine-human collective intelligence can create, decide, remember, and learn, in a number of different roles ranging from AI tools to support team working, and even AI managers who can help evaluate and

coordinate the work of others (Malone, 2018). Seeber et al. (2020) went further and suggested that effective AI teammates are more than social robots and digital assistants. AI teammates 'would be involved in complex problem solving: defining a problem, identifying root causes, proposing, and evaluating solutions, selecting suitable options, making plans, taking actions, learning from past interactions, and participating in after-action reviews' (Seeber et al., 2020). However, the concept of AI socialization faces several questions and challenges often centred around human perceptions on AI as teammates (Zhang, McNeese, Freeman, & Musick, 2021). These challenges include, teammate aesthetic, the division of labour and accountability, team dynamics and interpersonal communication among teammates.

AI-enabled systems will both automate and augment HRM decision-making in organisations, which has been a subject of debate, attention and fear in the community (Janssen, van der Voort, & Wahyudi, 2017). In this context, the existing literature has outlined concerns about the negative impact of AI such as bad decision-making, discrimination, bias, inaccurate recommendations, on the pace of adoption within the organisations (Davenport, Guha, Grewal, & Bressgott, 2020). Fear (AI replacing human jobs), negative perception (impacting decision-making and bias), limited trust on AI systems (how AI models work to generate responses) and skepticism (governance, ethics and morality in AI decision-making) among human workers has been also reported in the literature (Rampersad, 2020), and often debatable. There is limited consensus on the new jobs that will be created due to AI adoption, meaningfulness of these jobs, how roles and responsibilities of human workers will be redesigned, nature of AI-employee collaboration, and strategies to manage this change. Furthermore, clarification about the limits and advantages of AI will help organizations to successfully integrate AI in human working environment (Malone, 2018). The creation of knowledge within the organisations, sharing the knowledge to develop skills and capabilities among the human workers can help to decrease skepticism among human employees by promoting awareness and better understanding of AI systems, and AI-human role articulations (Klein & Polin, 2012). Wilson et al. (2017) and Malone (2018) have discussed the impact of AI on the workforce and how it will re-define the jobs, tasks and roles in a business organisation adopting AI technology to strengthen their analytical capabilities. Wilson et al. (2017) have proposed three distinct categories of jobs because of AI adoption within the business organisations, which will complement the capabilities of AI: (1) trainers will help to develop machine learning capabilities of AI-based intelligent tools by identifying data sources and input mechanisms to train AI systems which will enhance the reliability of the outputs generated by the AI algorithms and thus enhance the performance and productivity of these tools; (2) explainers will have the skills and knowledge to understand and interpret the output responses generated by the AI tools, assess the reliability of these responses and how they are being generated, and therefore enhance the trustworthiness of AI-based decision making in the business environment; (3) sustainers will ensure purposeful, effective, and fair usage of AI tools to alleviate reputational risks for the organisations posed by unintended consequences by developing a holistic AI governance structure based on ethical, accountable, moral and robustness of AI-based decision-making and usage of AI tools within the business processes.

The IM literature has reported that humans often reject and ignore a new technology, if they feel threatened by it (i.e., affects their financial and psychological wellbeing), irrespective of their interest and enthusiasm in it (Elkins, Dunbar, Adame, & Nunamaker, 2013). Barro & Davenport, 2019 have argued that although organisations have acknowledged the potential benefits offered by AI adoption, they are yet to augment human intelligence or replace employees with AI expert systems. This can be attributed to limited knowledge, skills and understanding among the workforce (both employees and managers) about AI capabilities, limitations, strategic initiatives, and integration with the existing business processes. The recent theoretical framework by Makarius et al., 2020 has discussed the role of AI as a collaborator (new employee), where AI-employee collaboration can help the organisations to achieve competitive advantage and business productivity. This can be achieved through AI socialisation among the human workers. Makarius et al., 2020 have defined AI socialisation as the process to introduce AI systems within the organisations by providing employees with AI knowledge, skills, and expectations pertaining to job roles and tasks involved in these roles. These will enhance ability of employees to trust, use and adopt AI, their own productivity, career satisfaction and development in the digital age.

3.3. AI and employment

Based on the review of existing research, we have identified the following essential skills required by human workers to easily adopt AI and benefit from its usage. (1) realisation skills will help to understand the capabilities and limitations of AI, which will facilitate understanding the benefits of AI adoption to solve specific business problems in a given context, and further identify the implication of using AI on business process/task re-engineering and productivity (Jöhnk, Weißert, & Wyrski, 2021; Pillai & Sivathanu, 2020) (Mikalef et al., 2020). (2) Utilization skills will require knowledge, expertise and understating (stemming from domain expertise) to interpret, explain and comprehend the outputs generated by AI-based decision support tools, which will help to augment data-driven decision-making in varying business contexts and problems (Chowdhury et al., 2022; Mikalef and Gupta, 2021). (3) Finally, maintenance skills are related to managing, governance and evolution of AI systems in a technology turbulent business environment. This is associated with sustaining the necessary digital and technical infrastructure, manage, and evolve it. In this context, domain expertise will help to understand the positive and negative consequences of using AI, develop a risk management plan to mitigate unintended and unfavourable consequences (firm and employee levels) and strategic interventions as well as policies to deploy AI tools within the organisation (Mikalef and Gupta, 2021; Makarius et al., 2020) It is envisaged that developing, managing, evolving and co-creating (with employees and external partners) these expertise and knowledge will stimulate and complement adoption, implementation and evolution of AI tools to create organisationally and employee-valued outcomes (productivity and resilience) (Younis and Adel, 2020).

Companies need to develop AI skills and expertise among their workforce to support the digital transformation (Trenerry et al., 2021). This will help to minimize the friction from the human workers, which could delay the adoption of AI, and subsequently impede

business value. The skills and expertise provide the organisations with capability to innovate, re-engineer and optimise both business processes and resources, efficiently, and dynamically adapt and remain responsive (Mikalef et al., 2020). Therefore, these skills are strategic intangible resources that will be difficult to imitate by other firms, providing competitive advantage (Barney, 1991). The technical and business skills necessary for each of the roles outlined above are two crucial components to drive AI adoption in organisations. These skills are crucial to bridge the gap between application of AI in a specific business context (how and why it should be used) and managing the implementation (clarity about how business processes, and human tasks will change) (Wilson et al., 2017).

The literature has on one hand argued and discussed that AI adoption within the organisations will increase the number of jobs (irrespective of some roles becoming redundant), while labour market and expert commentators speaking about job redundancies have failed to point out that new skills will be required among the workforce as a result of AI adoption. In this context, (Bughin et al., 2018) have argued against machine dominance and threat to human employment and suggest that early adopters of AI will need employees to grow their business, create value for their business and customers and therefore will stimulate employment opportunities. In this context, it is extremely important to understand that organisations have a critical role to play for developing capabilities among the workforce to work side-by-side with AI tools, and differentiate the capabilities of human intelligence compared to AI. This will significantly impact the existing organisational processes, nature and meaning of work, work design structure within organisations, competencies and skills required in specific roles within the digital workforce, technology exposure, employer and employee expectations, work practices within the organisation and human resource strategy to bridge the skills gap to increase employee motivation and productivity, which will lead to business productivity (Schroeder, Bricka and Whitaker, 2021; Wilson et al., 2017). In this context, a work design model reported in Connelly et al., 2021 helps to understand the impact of digital technology adoption and automation resulting from this adoption on organisational structure, task design, employee work environment and relational practices, and employee psychological immunity, which all are antecedents to business and employee productivity. Therefore, the model provides a strategic framework for organisations to understand the role of creating a conducive culture within the organisations to facilitate developing collective intelligence capabilities, where both AI and human workers can co-exist.

3.4. Drivers to AI adoption

Major drivers identified in the literature for the adoption of AI-enabled systems include the potential to be more objective, less likely to make mistakes, and the ability to predict future behavior through the identification of patterns in the historical datasets (Giermindl et al., 2021). AI can provide more flexibility and work-related autonomy, promote creativity and innovation, and allow to streamline organizational processes (Malik et al., 2021). For recruiting, AI can help writing job profiles, screening resumes, using enhanced video analysis to identify behavioral patterns of potential candidates, comparing them with the criteria required for the position, and identifying traits and skills of potential candidates to facilitate adaptation and enhance performance (Wilson & Gosiewska, 2014). Although it can reduce bias when screening candidates (Gaur & Riaz, 2019), there is a discussion in the literature stemming from the example of the recruitment tool of Amazon showing bias against women (Meechang, Leelawat, Tang, Kodaka, & Chintanapakdee, 2020).

Additionally, AI can be useful for monitoring, performance measurement and tracking employee morale (Gaur & Riaz, 2019). AI algorithms can be combined with techniques such as data envelopment analysis to identify underperforming employees, their impact on the efficiency and effectiveness of the company, and the overall performance of the organization (Panteia, 2020), AI can be combined with agent-based simulation to predict human resource development over time in a company to identify potential changes in recruitment strategies, the effect of promotion and development conditions, and the proportion of leavers under the conditions defined for the company (Pashkevich, Haftor, Karlsson, & Chowdhury, 2019). The use of AI for monitoring can also boost employee retention by analyzing social media data to identify employees interested on leaving and introducing interventions to prevent them from leaving the company (Gaur & Riaz, 2019).

AI capabilities can improve and optimize business operations and resources through task automation and augmenting human intelligence, which will reduce operational costs, lead production time, improve output/delivery response time (throughput), resulting in performance gains (Wamba-Taguimdje et al., 2020). The existing research has also indicated that IT adoption (such AI-enabled systems) within organisations will enhance dynamic capabilities which drives market capitalization, increased flexibility to re-engineer business operations and processes, resource agility, and responsiveness to address uncertain and evolving market demands and mitigate trade-offs within the organisation (Mikalef & Pateli, 2017). All these drivers will reduce bottlenecks and improve overall operational efficiency, which will result into superior business productivity.

Growing developments and usage of AI in everyday life and organisations has resulted in a need for HRM to consider the role and impact of AI on the well-being of employees. Issues such as bias (Chouldechova, Benavides-Prado, Fialko, & Vaithianathan, 2018), misinformation (Chesney & Citron, 2019), lack of understanding, intrusion, inequality (Buolamwini & Gebru, 2018) and labour displacement may negatively impact on employees' well-being and their feelings of security, trust and privacy. This has led to a standard of recommended practice for assessing the impact of AI on well-being (IEEE 7010, 2020), which aims to offer guidance for AI creators 'seeking to understand and measure direct, indirect, intended, and unintended impacts to human and societal well-being' (Schiff, Ayesh, Musikanski, & Havens, 2020). If handled appropriately, AI can offer a number of well-being benefits. For example, building well-being awareness, measuring well-being and the impact of interventions and changes, managing any AI risk on well-being, supporting positive well-being initiatives and providing employers insight into employee work-life-balance (Schiff et al., 2020).

3.5. Barriers to AI adoption

Tambe et al. (2019) argues that the adoption of AI for HRM faces four major challenges, namely the complexity of the HR phenomena, small data, ethical constraints, and the reaction of employees to the implementation of artificial intelligence. On top of that, Giermindl et al. (2021) and Malik et al. (2021) highlight the importance of privacy and data protection concerns, issues stemming from constant tracking, and the potential of bias in the algorithms themselves. Other barriers include, assessing the data quality to ensure the decisions and recommendations are precise, accurate and relevant (Ransbotham et al., 2020); optimal training dataset to reduce bias and reputational risks (Chowdhury, Rakova, Cramer, & Yang, 2020; Glikson & Woolley, 2020); integrating existing systems with the AI implementation, to streamline information processing and management (Kaplan and Haenlein, 2020); developing a data-centric culture within the organisation, so that everyone is onboard with the implementation and usage (Bieda, 2020); technology turbulence, i.e. pace at which technology is changing and disrupting business models and processes (Morse, 2020).

These barriers can have a significant impact in practice. There are several reasons why transparency is particularly necessary in a HR context (Chowdhury et al., 2020). An AI algorithm might identify a relevant criteria or relationship between criterion affecting the successful integration of employees into the company. However, that relationship may not be evident for decision-makers, which could question the reliability of the results (Meechang et al., 2020). For example, in the employee recruitment process, if the outcome of an AI algorithm is unfavorable for an applicant, the applicant and HR managers (unless they have been trained), have no mechanism for discovering why the applicant was unsuccessful, and consequently the applicant cannot knowingly improve his or her skillset. It is assumed in this argument that there is a way of controlling the input data and changing the outcome. This may not always be the case, as identified by Crain (2018), whereby transparency can be disconnected from power. This leads to the second area in which transparency is necessary, to address bias. In fact, several of the decisions made by humans are based on judgement and intuition (Meechang et al., 2020). Therefore, the interpretability of results from AI and the potential clash with the human perspective can hinder the successful implementation of AI. This is important because it highlights that the source of bias in AI is associated to the bias of the people implementing the AI.

Certain groups have been found to be disproportionality disadvantaged in AI algorithms, e.g., black faces associated as gorillas (Dougherty, 2015) and Asian people categorized as blinking (Wade, 2010). If a proportion of society is consistently marginalized in the job market or in a particular organisation, HR managers need to answer user and societal questions. If users or HR managers do not understand the algorithms' affordances and variants, this can result in an inability to use the algorithms effectively to recruit and retain the best possible staff and to be swayed by prejudice (Chowdhury et al., 2020). It should not be acceptable that 'blame' for such inappropriate outcomes such as prejudice fall upon a 'mathematical model'. Ownership of the AI algorithm and its results may be placed on HR managers, and as such they would need to know the rationale for the data input choices and results (Davenport & Ronanki, 2018).

For HR recruitment the decision-making process of targeting potential candidates and taking them through the rudimentary checks, is accelerated using AI. However, this raises significant questions about quality of the process itself, in particular an epistemological issue regarding the reliance on digital quantitative data from which the AI algorithms learn (Faraj, Pachidi, & Sayegh, 2018). Case in point, the HR recruiters are relying on the meta-data available on social media outlets to target potential candidates for roles within organisations. The lowering of costs and easy access to the digital world, coupled with relative ease with which vast amounts of meta-data can be processed, has led society to become dominated with the logic of quantification (Espeland & Stevens, 2008). This quantification has become a substitute for an individual's social life, personality, abilities and choices, attributes upon which recruitment decisions are being made. While the algorithms can predict with some precision individual attributes and characteristics, it also limits the recruitment pool by choosing a particular set of characteristics to target. Further, learning algorithms are reductionist in nature as they use predictive modelling based solely on correlational analysis of measured dimensions, thus reducing the individual to only those measured criterion (Faraj et al., 2018). Thus, reducing individuals to a set of measured dimensions and avoiding dealing with a person's evolution and alternative explorations that may explain how one ends up in specific category (Ananny, 2016). This inevitably raises questions about overreliance on AI decisions regarding targeted recruitment and following recruitment processes.

Additionally, AI is assumed to have shortcomings in creative and social intelligence (Mak, Li, Tang, Wu, & Lai, 2020). For instance, AI has the potential to identify areas of lower performance based on the achievements of employees, but it would struggle to process the underpinning factors leading to low performance and therefore it could interpret a need for action in instances that may be temporary or affected by external variables. The effect of those external variables is in fact another key barrier for the use of AI. The predictive capacity of AI can be hindered by the challenges to accurately describe the complexity of human behavior (Pashkevich et al., 2019) and the effect of unknown external effects affecting the conditions of the environment and the company itself. The complexity of incorporating uncertainty in the environment (e.g., the COVID-19 contingency) and the inability to accurately predict human behavior represents a challenge for the predictive capabilities of AI. Therefore, the capability of AI needs to be combined with the capacity of humans to empathize and understand the results within the global, organizational, and personal context. In this way, humans become gatekeepers leveraging the potential from AI (Wang, Zhang, & Guo, 2021) to use the findings in the most appropriate way, thereby augmenting decision-making. This will also require human operators to constantly review, revise and update the parameters in the AI algorithm to account for organizational changes such as shifts in priorities and inclusion of relevant criteria for external stakeholders. Such initiatives will lead to successful AI implementation and acceptance from decision makers for its subsequent adoption (Cao, Duan, Edwards, & Dwivedi, 2021).

4. Framework development

The aim of this review is to coalesce both the popular and under-researched research themes exploring the links between AI and HRM. The framework put forward (Figure:2) seeks to illustrate the multiple resources required to build capability to integrate AI into

Table 2
Resources to develop AI Capability

Resource Type	Resources	Description	Reference
Technical Resources	Data resources	Internal data from internal operations. External data from stakeholders, suppliers and market environment. Data collected using sensor-based technology, existing HRIS and ERP, enterprise social media and public facing social media	Keding, 2020; Pumplun, Tauchert, & Heidt, 2019; Schmidt et al., 2020; The Economist (2020)
	Technology infrastructure	Data storage, data management, data cleaning and aggregation, processing power (parallel computing), network bandwidth, cloud-based solution, algorithms and software programs	Wamba-Taguimdje et al., 2020; Borges, Laurindo, Spínola, Gonçalves, & Mattos, 2021; Wang, Huang, & Zhang, 2019
	AI transparency	Learning algorithms, software such as Local Interpretable Model-Agnostic Explanations (LIME) AI design infrastructure,	Shin & Park, 2019; Zhang, Song, Sun, Tan and Udell, 2019; Chowdhury et al., 2020; Silverman, 2020
Non-technical resources	Financial Resources	Access to capital, internal budgeting, financial resource allocation to experiment and validate AI solutions, before adoption. Budget allocation for employee skills development and facilitating career development	Fleming, 2019; Mikalef & Gupta, 2021.
	Time requirements	Periods for experimentation, achieving maturity in the sense of moving beyond proof-of-concept solutions, yielding value from adoption gradually over a period	Chui et al., 2018; Fleming, 2019; Mikalef & Gupta, 2021.
	Technical skills	Support implementation and development of AI solutions, primarily, statistical, programming, design thinking and data business analytics skills.	Wilson et al., 2017
	Business skills	How and where to apply AI, understanding capabilities and limitations of the technology, business process modelling, interpreting AI response, governance and management of AI solutions.	Ransbotham, Khodabandeh, Fehling, LaFountain, & Kiron, 2019; Ransbotham, et al., 2018; Fontaine et al., 2019.
	Leadership	Resource allocation, providing capital funds, understanding the needs of employees, business goals and priorities, strategic orientation, develop good working relationships with employees and teams, follow clear communication mechanisms	Chui et al., 2018; Davenport & Ronanki, 2018; Koh, Lee, & Joshi, 2019
	Culture	Foster collaboration, conducive working environment, encourage creativity and innovation, risk-oriented approach meaning developing a culture which is agile, experimental and adaptable to the needs of the market and that of the human workers,	Mikalef & Gupta, 2021; Lee et al., 2019; Fontaine et al., 2019; Ransbotham et al., 2018; Ransbotham et al., 2019
	Co-ordination between teams	Common understanding and shared vision between the employees working in different teams, whether impacted or not impacted by AI adoption, to develop mutual goals and collaborative behaviour.	Fontaine et al., 2019; Ransbotham et al., 2018; Mikalef & Gupta, 2021
	Organisation change	Ability to respond to change with minimal friction from employees which does not impede business growth, ability to plan, communicate, strategize and manage change to realise performance gains (it will depend on leadership, culture, co-ordination between teams, employees' skills and knowledge)	Pumplun et al., 2019; Ransbotham et al., 2020
	Knowledge management	Mechanisms and strategy to create, share, co-create, store, evolve, communicate, and apply knowledge individually by employees, and collaborating with other employees to enhance their understanding, capability, creative intelligence and innovation mindset	Chowdhury et al., 2022; Mikalef et al., 2020, Makarius et al., 2020
	AI-employee integration	Develop collective intelligence capability within organisations through AI socialisation, informing employees about the adoption strategy, seeking their views, involving them in the implementation process, clarifying job roles, responsibilities and expectations, job autonomy and job characteristics, providing a clear path for career progression to enhance employee psychological outcomes and productivity (it will depend on knowledge management and AI adoption strategy, and impacted by leadership, culture and co-ordination between teams).	Bieda, 2020; Makarius et al., 2020; Amabile, 2020; Chowdhury et al., 2022
Governance and regulation	Embed ethical and moral principles governing implementation, utilization, and evolution of AI-based solutions in the CSR strategy to address issues related to bias, inaccuracy, opacity, accountability, safety and security, societal and environmental well-being. Deciding when to use AI and when to rely on human judgement (also guided by the context of using AI). Defining protocols for the secure management of information managing data privacy and data protection.	Demlehner & Laumer, 2020; (European Commission 2019a and 2019b; Arrieta et al., 2020	

HR processes and practices within the context of a firm. We demonstrate the impact of these transformations on the business organisations, derived from the literature in this area. The framework draws upon and integrates the theories of resource-based view (RBV) and Knowledge based view (KBV). This is particularly relevant as both RBV and KBV are important lens to study developing new capabilities in organisations (Grant, 1996; Chahal, Gupta, Bhan, & Cheng, 2020)

RBV is one of the most widely applied theoretical perspectives to explain how resources within an organisation can help to enhance business performance and competitiveness (Barney, 2001). The existing literature has also demonstrated appropriateness of RBV to be applied as a theoretical lens for developing distinctive and hard-to-imitate capabilities (such as AI implementation) in a turbulent and technology-driven business environment (Mikalef & Gupta, 2021). Knowledge based view (KBV) theory draws from classical management theories, is often considered as an extension of the RBV theory, and posits that knowledge created within the organisation is a critical asset which will help to produce sustainable competitive advantage in dynamic market environments because: (1) knowledge-based sources are socially complex to understand and embedded within the firm; (2) difficult to imitate by another organisation; (3) continuously evolve and often co-created within the organisation (Grant, 1996). Although, KBV does not specify mechanisms to share knowledge that will promote and satisfy individual-level outcomes, knowledge management literature (Hansen, Nohria, & Tierney, 1999) has outlined strategies such as codification and personalisation to enhance knowledge sharing mechanisms, initiatives, and interventions to achieve organisationally valued benefits. Consolidating these theoretical perspectives will help to critically understand how internal resources (satisfying the valuable, rare, inimitable, non-substitutable, VRIN in short) within an organisation and not just technical resources can facilitate enhancing capabilities, competencies, and business competitiveness to adopt, implement, deploy, and evolve AI-based solutions

The organisational resources derived from the themes (AI drivers and barriers, and collective intelligence) are listed in Table 2 (Fig. 2). These unique resources represent the basis for defining the organisational readiness to utilize AI (i.e., resources that need financial investment and time to develop) and how it will be used (i.e., context which will lead to business process transformation). The framework further integrates these organisational resources with the themes identified in the review (AI applications, collective intelligence, and AI employment). The context of use will depend on the specific characteristics of the firm and the problems faced. We envisage the context will also determine type of AI (automation, augmentation and assisted). We have not included autonomous intelligence because we are yet to come across such an AI system in HRM, which can function without any human involvement. We argue that bots (chat systems) are based on rule-based systems, and often monitored by humans, given the risks associated with them e.g., sexist - (BBC, 2020), and racist remarks - (Cheuk, 2021), which can negatively impact an organisation’s reputation. This leads us to the next piece of the puzzle, i.e., impact on human workers and traditional HR structure within organisations, stemming from AI-Human collaboration (collective intelligence). The impact on employees is shaped by various factors such as: type of AI, particular process where it is used (e.g., recruitment, payroll), overarching AI strategy of the organisation, knowledge creation and dissemination related to AI and finally existing effort to develop skills, knowledge, and expertise of employees. The development of skills and expertise in-house will provide role clarity in a collaborative AI-HI working environment, develop trust and confidence among the human workers, which will enhance their emotional engagement with AI, and lead to superior business performance (Chowdhury et al., 2022). In the context of AI knowledge sharing, codification will facilitate scaling up the knowledge dissemination across the organisation and re-using the knowledge, and personalization will promote trust and cooperative attitude of employees towards AI, through networking and discussion. These strategies and initiatives will facilitate in developing an organisational culture which fosters

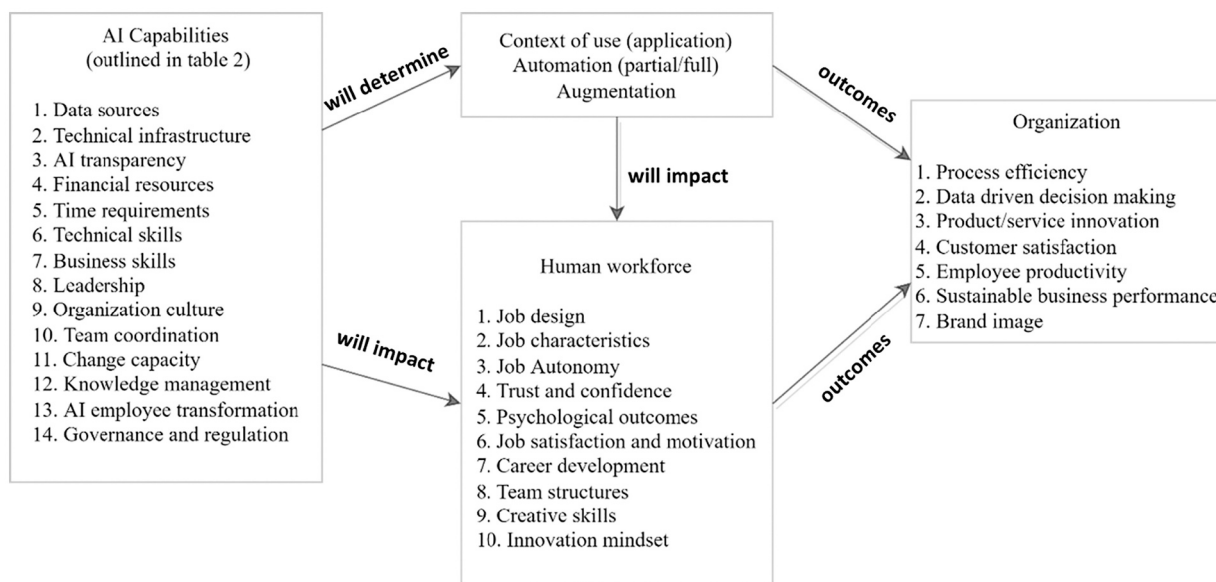


Fig. 2. Framework summarising the review findings

creativity, innovation capability, collaboration between teams, less resistance to change and conducive to the needs of human workers (where their human attributes such as intuitive intelligence, empathy, negotiation, and communication skills are acknowledged).

Finally, the evidence from the literature alludes to increased productivity benefits from acceptance of AI process within the workplace by employees. This takes the form of: (1) process efficiency, which will help the employees to focus on non-trivial tasks requiring their business expertise and creative intellect (Mikalef & Gupta, 2021); (2) generating hidden patterns and unlocking useful insights from big data facilitating data-driven decision-making efficiently (Lichtenthaler, 2019); (3) introducing new products and services, improving the quality of existing ones positively impacting operational performance (Wamba-Taguimdje et al., 2020); (4) customer satisfaction by proactively understanding their needs, preferences and both positive and negative experiences (Davenport & Ronanki, 2018); (5) environmental performance by reducing energy consumption and greenhouse gas emissions, re-using resources (Borges et al., 2021); (6) social performance by reducing human subjective bias in HR processes such as recruitment, employee appraisal, and improving employee experience and working conditions by analysing enterprise anonymous social media data (Tonio, Masiero, Massaro, & Bagnoli, 2020); (7) economic performance realised through business growth and revenue generation from 1-5 listed above, optimal employee turnover as a result of effective knowledge management strategies and 6 listed above, and ability to dynamically adapt AI innovation and re-engineer processes; (8) developing successful business cases related to AI implementation which will enhance reputation among the business stakeholders, competitors, policy makers and consumers.

5. Discussion and research propositions

Considering the systematic review of literature and the AI capability framework, we present five key research priorities and associated pathways that will help develop conducive organisational context and effective strategies to adopt AI in HRM. In doing so, we also identify emerging research areas considering the most recent developments and advances in the adoption and implementation of AI-enabled applications for human resource management.

5.1. AI organisational resources

While existing studies have focussed on applications of AI, potential benefits, and perception among the business users and consumers (Makarius et al., 2020), there is a gap in literature empirically examining the organisational resources that are required to develop firm-specific and unique AI capabilities. Our review illustrates the importance of understanding complementary organisational resources required to benefit from AI adoption in HRM, and exploring beyond the data and technological resources (Mikalef & Gupta, 2021). This underscores the need to adopt a holistic approach to develop AI capability in the organisations as investment on technology alone is unlikely to result in business gains. In this context, we have presented the AI capability framework outlining the resources required to utilize AI effectively within the core HRM operations. While we have integrated RBV and KBV to objectively develop the framework considering both technical and non-technical resources, potential impact of the proposed capabilities on organisational creativity, innovation, dynamic capability, and business productivity warrants empirical investigation. Given the interpretive nature of some of these outcomes, a mixed method approach to discern the role of organisational resources relevant for AI adoption and the outcome variables (creativity, innovation, dynamic capability, and productivity) is proposed (Bell, Bryman, & Harley, 2019). Based on this discussion, we propose the following research questions.

- A1: What is the relationship between the organisational resources required to adopt AI in HRM processes and organisationally valued outcomes such as creativity, innovation dynamic capability and sustainable business performance?
- A2: How can organisational resources be prioritized in their impact on successful AI adoptions within an organisational context of utilization, priorities, and business goals

5.2. 'Behind the Algorithmic curtain': Issues of AI transparency and access

One of the core issues regarding the use of algorithms in making key organisational decisions is the inscrutability of the decision-making process that the algorithm engages with to arrive at the outcome (Faraj et al., 2018). For example, big tech companies like Facebook, Google and Amazon design algorithms that contributes to their success, however, these algorithms are closely guarded and protected as intellectual property (O'neil, 2016). Further, even if the algorithm were designed by the firm for its own purpose, the learning capability of the algorithm eventually makes it impossible to discern the process of how the decision was reached. Even if auditing were to be applied to such algorithms, understanding them would be limited only to a select professional class of knowledge workers with highly specialized skills and technical training for comprehending code of immense size and logical complexity (Dourish, 2016). This inscrutability of the algorithm lends itself to an inherent lack of transparency in the use of AI within the organisational context. This lack of transparency is echoed by other scholars who argue that the inherent lack of transparency in the process of decision making by AI, makes organisational agents hesitant about using AI for important decisions (Schmidt et al., 2020). However, the organisational behaviour and psychology literature also suggests that individual's intention to use AI for decision making is dependent on perceptions and beliefs about technology (Ajzen, 1991), which would suggest that there would be a demographic divide in openness to AI. Equally, further expansion of models to delineate motivations and drivers for AI use have come back to the issue of trust and transparency of the AI systems. The findings from our review shows that research studies examining the domain of AI transparency and its impact on workplace trust is extremely limited in the HRM literature. In the context of data-driven decision-making, the issue with explainability is that business managers do not know how AI-based machine learning (ML) algorithms generate

the outputs by processing the input data because the algorithm is either proprietary or that the mathematical computational models used in the algorithm are very complex to understand (Shin & Park, 2019). Limited transparency and explainability of output responses generated by the AI systems has emerged as a key barrier to experiencing anticipated benefits by confidently turning data-centric decisions into effective actionable strategies (Makarius et al., 2020; Shin & Park, 2019). We propose following streams of research that will help advance our knowledge in this area

- A3: Which organisational resources (both technical and non-technical) are needed to enhance AI transparency and accessibility?
- A4: How will enhancing transparency of AI algorithms impact the decision-making strategy and perception of both employees and HR managers in business organisations?

5.3. Knowledge sharing: AI-employee collaboration

The existing literature and our review have outlined several benefits of using AI tools and systems such as superior analytical capabilities to process big datasets which have facilitated forecasting clinical demands during the ongoing pandemic (Islam et al., 2021), and tools to support agile and effective decision-making in HR processes (Daugherty et al., 2019; Davenport & Bean, 2017). Despite the known benefits of using AI tools, majority of the organisations have failed to experience the organisationally valued outcomes (productivity) (The Economist, 2020 and Deloitte, 2017). This is often attributed to organisations facing difficulties to effectively, strategically and seamlessly integrate AI systems with existing human workers, processes, workflows, information systems and business strategies (Deloitte, 2017). In this context, there is a lack of both understanding as well as expertise on the best practices to effectively develop collective intelligence capability, where humans can leverage AI within organisational tasks and workflows (Chowdhury et al., 2022; Makarius et al., 2020). Our review has found that the adoption of AI within HRM processes and wider organisational workflows will impact employees in different ways, such as job substitution, skills and expertise development needs, and uncertainty regarding roles and responsibilities (Frey & Osborne, 2017), limited understanding about how and why AI will be used in a given context (Raisch & Krakowski, 2020), trust and confidence in AI usage (Gunning & Aha, 2019), formation of project teams where AI and HI may need to co-exist as teammates (Parry, Cohen, & Bhattacharya, 2016), concerns about career progression and development (Makarius et al., 2020). All of these are likely to result in negative perception and employee productivity, skepticism, and psychological detachment with regards to AI adoption and implementation (Makarius et al., 2020).

The knowledge gap is situated in this interpretive-objectivist nexus, how will the use of AI foster or impede employee collaboration and knowledge sharing. In this context, research has shown that knowledge management practices (sharing, creation, co-creation, storage etc.) in the organisations will lead to knowledge integration and evolution which will enhance organisational dynamic capability and business competitiveness (Kearns & Sabherwal, 2006; Nickerson & Zenger, 2004). However, the impact of knowledge management strategies and practices on AI-employee collaboration needs further empirical investigation, particularly in light of intangible employee attitudes of trust and psychological contracts. We propose following streams of research that will help advance our knowledge in this unknown and uncharted territory to facilitate organisations with evidence-based practices, strategies, and interventions to enhance AI-employee collaboration.

- A5: What are the boundary conditions in terms of employee attitudes that are required to ensure employee collaboration following introduction and continued use of AI processes in the workplace?
- A6: How can knowledge management strategies enhance collaborative intelligence capability within the organisations? What are the external resources required to effectively develop knowledge within the organisations, for e.g., considering the institutional view of firms?

5.4. Learning and development for use of AI at work

HR practitioners need to have certain AI skills and knowledge to effectively use the technology to its capacity. Malik et al. (2020) have suggested that HR practitioners need to develop analytical skills and an overall understanding of the business, further, an understanding of research design and data capture and processing, and identifying business needs for continued AI development and improvement. Moreover, the management of these competencies, skills and knowledge is considered an asset for organisations that can be supported using AI (Younis & Adel, 2020). The skills and expertise provide the organisations with capability to innovate, re-engineer and optimise both business processes and resources, efficiently, and therefore can their ability to dynamically adapt and remain responsive (Mikalef et al., 2020). Ideally, they should also help to govern and regulate AI, which will ensure that the business code of ethics is adhered. A recent study has reported that data analysis, digital, complex cognitive, decision-making, and continuous learning skills are necessary for AI adoption in multinational corporations in India (Jaiswal, Joe Arun, & Varma, 2021). Organizational structural issues will be influenced by AI systems in a variety of areas that are yet to be examined. Considering the new set of skills and capabilities needed for managers, employees, and AI to collaborate, there will be a necessity to redesign jobs, create new ones, transform business model and strategies (Toniolo et al., 2020; Wamba-Taguimdje et al., 2020). Considering, the need to reskill and upskill human workforce, we propose the following research questions which will advance the capabilities of both human workers and organisations to benefit from AI adoption.

- A7: What are the factors that will help to determine skills, competencies and knowledge required by employees and managers for successful engagement with AI processes within the workplace? In this context, how can organisations, higher education institutions and policy makers collaborate (i.e., what will be the role of each stakeholder) to either reskill or upskill workforce?

- A8: *What will be the influence of reskilling and upskilling employees on AI adoption and creating an environment where human intelligence and AI will co-exist? In this context, what is the relationship between skills development and job design and AI adoption?*

5.5. Sparsely researched niche themes

We found that recent reports published by the European Commission have emphasised on ethical and moral aspects surrounding AI, which has led inclusion of these criterion in development and use of AI (European Commission, 2019a and 2019b). The aim here is to minimize potential risks faced by organisations with regards to using AI and simultaneously protect the interests of business users (and/or whose data is collected) (Arrieta et al., 2020; Coombs, Hislop, Taneva, & Barnard, 2020). While research in this area is slowly emerging in fields other than HRM (Bhave, Teo, & Dalal, 2020), future studies must examine and explore strategies and principles that will help organisations to align AI utilization with their core ethos and values. In this context, we propose the following pathway.

- A9: *How CSR principles and strategies within organisations can help account for AI ethics, governance, and regulations? What will be the implications and challenges in deploying AI within HRM processes (for e.g., workforce analytics, also considering data protection principles, such as European Union General Data Protection Regulation) and in a regulated environment.*

Finally, most studies reported in the literature and including HRM focus on multinational large organisations. According to world bank, SMEs represent about 90% of businesses and more than 50% of employment worldwide, and therefore play a major role in job creation and global economic development (World-Bank, 2020). They are also considered essential drivers of innovation in both developed and developing economies. In emerging markets, most formal jobs are generated by SMEs, which create 7 out of 10 jobs (World-Bank, 2020). In this context, research studies are yet to examine adoption of AI within SMEs, and considering various constraints faced by these enterprises such as access to finance, human resource skills and flattened HR structure, resource constraints and limited knowledge management tools. Along similar lines, we believe that the adoption of AI within HRM will also vary according to geographical regions (developed and developing economies) and industry sectors (such as manufacturing, construction, services, education creative industry and tourism) (Vrontis et al., 2021). We are yet to find cross-country and cross-sector studies examining factors influencing AI adoption. For e.g., while many studies have examined perceptions of employees and managers, cross-country/cross-sector comparisons will bring new insights from International HRM perspective. Based on the above discussion, we propose the following research streams.

- A10: *How do country-specific institutional determinants such as culture, regulations, and market environment, impact the dynamics pertaining to adoption, implementation, and evolution of AI applications in HRM? In this context, what are the drivers and barriers to AI adoption from the perspective of different stakeholders (managers, employees, consumers, policy makers and technology providers)? A similar study can be conducted to compare business sectors.*
- A11: *Can SMEs benefit from AI adoption? What are the key drivers and barriers for SMEs organisations to utilize AI-enabled solutions within their business processes? What are the resources required by SMEs to overcome these barriers?*

6. Conclusion, implications and limitations

The aim of this paper was to conduct a systematic review of literature concerning the state of AI research in HRM. We reviewed potentially relevant studies in top-tier HRM, GM, IB and IM journals, and based on the inclusion criteria as well the research question. The review has identified following key themes in the literature: *AI applications* in HRM; *collective intelligence*; *AI employment and skills*; *AI drivers and barriers* to adoption. We found that the current literature has primarily focussed on the applications of AI in HRM, anticipated benefits, impact of AI on jobs, and AI-driven decision-making augmenting human intelligence. However, research on collective intelligence stemming from AI-employee collaboration, AI transparency and explainable analytics, and AI ethics and governance is nascent and emerging within the HRM literature. While, many studies have reported the drivers and barriers related to adoption and implementation of AI, we consolidate these multi-disciplinary perspectives, and integrate RBV and KBV theories to propose AI capability framework. The capability framework will help managers in the organisations assess their readiness to leverage AI-based systems. Based on the systematic review, we also propose research priorities for theoretical and empirical advancement of scholarship on AI in HRM. The research priorities identified are: (1) validation of the *AI capability framework* (resources and knowledge); (2) impact of *AI transparency and trust* on employee and business productivity; (3) antecedents to *AI-employee collaboration* and its impact on business performance; (4) knowledge management strategies to *upskill and reskill workforce*, and its impact on AI-employee collaboration. Our review findings show the need to undertake empirical studies to provide conclusive evidence showing the impact of AI adoption on employees, managers, HRM processes, and business productivity. These studies should be developed on the conceptual work reported in the existing literature by adopting multi-disciplinary and multi-theoretical perspectives to enhance impact of the findings and research rigor.

6.1. Theoretical implications

From a theoretical perspective, firstly, we contribute to shaping the narrative of the current debate on AI adoption in HRM and its impact on human jobs in organisations which are likely to be disrupted by AI. Further, we put forward some areas of knowledge that can shape organisational strategies for AI-employee collaboration (where both AI and human intelligence will co-exist). This will

facilitate development of strategies and capabilities within organisations to build hybrid workforce in the future, that has the potential to enhance business performance, and dynamically adapt to market uncertainty and volatility (Chowdhury et al., 2022). In this context, our review had identified that the anticipated benefits of AI in HRM processes and practices can be realised by developing collective intelligence capability within the business organisation. The existing research studies have indicated the importance of AI-human collaboration (Chowdhury et al., 2022; Makarius et al., 2020), which has emerged as a new research theme in the literature. Research on this theme is less developed in the management literature, except Makarius et al., 2020 reporting an AI socialisation theoretical framework. The importance of collaboration, cooperation, and coordination, to understand the capabilities and limitations of AI in the organisational settings has been discussed in (Caputo, Cillo, Candelo, & Liu, 2019). The authors have concluded that effective collaboration between human intelligence and AI will help to unlock the real potential of digital technology to solve pressing business and societal challenges, and this will require careful crafting of a strategy to re-define and recategorize existing jobs, by considering the skills-gap.

Secondly, our review found that developing appropriate conditions, strategies, and resources within the organisation will allow the employees to harness AI skills, facilitate access to relevant knowledge and expertise base, and therefore will facilitate AI adoption and implementation within the business processes. According to Lei, Gui, & Le, 2021 have reported that the motivation and willingness of employees to embrace change, innovation, dynamically adapt and evolve is guided by a supportive and sharing culture within the organisations. In this context, organisational leadership will play a significant role in developing and shaping a positive culture and innovation mindset within the organisations, which is conducive to introducing, implementing, and managing innovation (such as AI) within the organisations (Le, 2020). Therefore, AI can be considered as an innovative technology and organisational strategies put forward by the managers will play a critical role to develop facilitating conditions to deploy, manage and evolve AI.

Thirdly, our review shows that explainable analytics, i.e., understanding how AI algorithms generate recommendations based on the inputs will facilitate building trust among the managers and turn these outcomes into meaningful and actionable insights (Cowgill & Tucker, 2020). The ability to understand the output responses will also reduce biases in business processes, operations, and decision-making, thus enhancing fairness (Satell & Sutton, 2019). The aim of transparent and explainable AI is for the business users to confidently assess the reliability and accuracy of the output responses based on their own tacit domain expertise, which will augment trust in these systems. Therefore, embedding transparency in AI algorithms will facilitate better understanding and confidence in AI system. This will lead to faster adoption of AI-based systems within the HRM processes and practices, and in true sense augmenting human intelligence (i.e., human will be able to trust these systems).

Finally, we propose the AI capability framework consolidating the drivers and barriers related to AI adoption in business organisations, derived from multidisciplinary literature. In this context, we have used a multidimensional theoretical approach consolidating knowledge-based view (KBV), and resource-based view theory (RBV) to objectively identify the technical, non-technical and human-centric resources required by organisations to adopt and implement AI. In doing so, we follow the calls and directions in the extant literature to examine the development of AI and implications in HRM, building on the research reported in multiple fields of business and management, including IM and OM (Budhwar & Malik, 2020a, 2020b; Vrontis et al., 2021). While, IM research has primarily focussed on technical resources and infrastructure required to adopt AI, and wider business and management studies have focussed on non-technical resources, our capability framework objectively brings these two rather fragmented pieces of literature together. Therefore, the framework provides a comprehensive understanding of all the organisational resources necessary to strategize AI adoption. The multidimensional theoretical approach also considers the cognitive, structural, and relational implications of AI-employee integration, which has been highlighted in the existing literature (Makarius et al., 2020), meaning that we do not view AI as a stand-alone technology which will solve all business problems. On the contrary, AI is a technology and its adoption, implementation, and impact within HRM will depend on other resources and organisational strategies operationalising and governing these resources. Although, our findings may be viewed as antithesis to overinflated benefits of AI reported in the media, our review shows that the business value and tangible benefits resulting from AI adoption in HRM is still inconclusive in the academic literature.

6.2. Practical implications

Our review has several implications for managers. Firstly, the AI capability framework proposed in this article can be used by HRM practitioners to assess the readiness of the organisations to adopt and implement AI systems. In doing so the framework will help to objectively identify both technical and non-technical resources required to operationalise AI systems. Our review found that albeit the technical resources, managers need develop appropriate strategies, communication mechanisms and interventions that will foster coordination, mutual understanding, collaboration and cooperation between departments, project teams and employees (Mikalef & Gupta, 2021). This will facilitate mobilization and orchestration of AI within organisations and HRM processes.

Secondly, knowledge sharing mechanisms within organisations need to be strategized by the managers to facilitate development of skills, competencies, and knowledge among the human workforce in the context of adopting and utilising AI-based systems. These strategies must aim to develop an organisational culture that enables interdisciplinary collaboration, interdepartmental co-ordination, data-driven decision making, shared and common understanding between employees, experimental and adaptable mentality, risk-oriented approach (rather than risk-averse strategic orientation). According to Fountaine et al., 2019 and Davenport & Ronanki, 2018, organisations should develop their own innovation ecosystem (i.e., using the resources available and further developing capability within the organisation). This ecosystem can follow a hub and spoke model, where 'hub' is responsible for AI governance and regulations, determining AI-employee collaboration strategy and initiatives, and managerial responsibilities, while 'spokes', will handle responsibilities closer to the use of AI (i.e., interpreting AI outputs and training AI systems) (Fountaine et al., 2019). In this context, our review shows that innovative culture will stimulate employees to embrace AI, identify and seize new opportunities to use

AI through their creative intellect, and dynamically respond to change resulting from HR business process and practice transformation, which will help to enhance business productivity and competitiveness. AI systems will extend beyond the current capabilities, therefore albeit knowledge creation, co-creation and sharing, evolving the knowledge is equally important to remain updated and competitive in the highly turbulent AI technology environment.

Thirdly, to alleviate negative perceptions and skepticism around AI adoption in human-centric business processes, managers need to establish clear and transparent communication strategies and dialogues with the employees. The aim should be to clearly outline the AI adoption and change management strategy, its impact on job design, roles and responsibilities of the employees, expectations from the employees, purpose of using AI, its capabilities and limitations. Our review has outlined that better understanding of AI adoption context, and enhance trust and confidence in the management initiatives and strategy (Davenport & Mahidhar, 2018). This will also require the managers to develop their own knowledge and understanding with regards to capabilities and limitations of AI, since AI-based solutions will be operationalised according to their organisational business process transformation strategies, contextual design directives and financial investment.

Finally, our review shows that understanding the capabilities, scope and limitations of AI to solve the business problems are critical elements for developing the AI digital strategy, which must be driven by potential impact that the AI implementation (Ransbotham et al., 2018). In this context, HR managers should consider the following dimensions to develop the AI digital strategy: (1) business case to adopt AI, i.e. problem scope to utilise AI; (2) business process analysis to identify the changes within the existing workflows resulting from AI adoption; (3) digital readiness assessment both in terms of digital infrastructure and competencies of the human workforce; (4) data management strategy, i.e. availability of existing data, requirement to collect/store new data, data governance and ownership; (5) decision to buy off-the-shelf AI system or develop the solution in-house; (6) multidisciplinary team having variety of skills, domain expertise, digital experience and providing complementary viewpoints, supporting the technology team involved in AI implementation; (7) strategy to develop data-centric culture within the organization, where technology is used as driver to augment human tasks and intelligence; (8) integrating design thinking and agile methods to make employees an integral part of the development/implementation team, which will help employees to understand the implications of AI adoption; (9) AI governance policy which will put emphasis on accountability; explainability of the automated decisions; fairness, data rights of the user, to have a clear understanding of how and why AI is being used; (10) periodic assessment of the AI systems (i.e. whether the existing strategy fulfils the KPIs and business goals), initiatives to maintain the systems, and customize, evolve and adapt according to the dynamic market and competitive environment.

6.3. Limitations

Our review has few limitations, which can be adequately addressed in future. Firstly, our review is restricted to studies published in top tier peer reviewed journals (ABS ranking – 3, 3*, 4 and 4*). We believe studies published in lower ranked journals, non-peer reviewed articles (e.g., *The Conversation*), and practitioners' literature (e.g., reports published by business consultants) can further enhance our understanding to make the knowledge synthesis more rigorous. Secondly, our search (using the selected keywords and Boolean operators) may not have identified all the articles relevant to the topic due to issues related to database unavailability or human error. We believe future research should also include other repositories such as Web of Science, DBLP, Social Science Research Network (SSRN) and SpringerLink, to extract new articles from multiple disciplines further advancing the AI scholarship. In this context, we believe that including databases publishing law journals can facilitate comprehensive review of the literature on the theme of AI governance, ethics and regulations in HRM. Finally, while, in this review we relied on the judgement of academic experts and the existing academic literature to select the trending themes of AI research in HRM, research propositions (i.e., under-researched and emerging areas in the field), and resources to develop AI capability within organisations. Future studies can build on these findings by capturing empirical evidence from HR business practitioners to further validate the trending themes and determine the importance of research propositions. The importance of research propositions can be determined through interviews or Delphi-study, and then analysing the quantitative data using AHP. Such an initiative will bridge the gap between academic findings and perception of HR practitioners, to develop research agenda aligned to the needs of both industry and society.

Author statement

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Appendix A. AI Applications in HRM

Context	AI application	Selected References
1-Candidate Experience (job applications)	Digital virtual assistant (chatbots) can respond to candidate queries in real-time and quickly, thus eliminating the need to email HR, help them learn about the organisation and the job role, show employees working in similar job roles, automatically pre-screen candidates analyze job matching using candidate resume, and therefore attract and identify high quality candidates, providing feedback to candidates to demonstrate efficient and fair review process, therefore building trust among the applicants, and thus enhance their candidate experience	van Esch, Black, and Arli (2021) Upadhyay and Khandelwal (2018)
2-Candidate Recruitment	Digital virtual assistant can pre-screen the candidate based on the resume and other information. Machine learning enabled AI application integrating video scanning technology can recommend questions to the recruitment panel during the interview and provide recommendations considering the resume and interview performance to the recruiters (summarizing the profile of each candidate and comparing the profiles of all candidates). Predict the likelihood of a candidate accepting an offer, project future performance of the candidate by learning from historical similar profiles and similarly predict the expected tenure (i.e., likelihood of candidate leaving the organisation after 'n' years)	Upadhyay and Khandelwal (2018), Van Esch et al. (2019)
3-Onboarding	Digital virtual assistant can quickly answer questions, guiding the new hire through the steps, making them aware of their role and tasks, helping them complete mandatory training, capture information about the employee skills and recommend job-related learning content based on employees in similar roles.	Babic, Chen, Evgeniou, and Fayard (2021)
4-Employee engagement	Personalized experience to the employees customized to their daily needs and routine tasks as well as schedules by automatically managing calendars, scheduling meetings, answering queries efficiently, just in time recommendations and alerts facilitating decision making, improve engagement within a team, effectively collaborating across teams (individuals working in similar roles, having similar profiles, career progression), assigning mentors.	Wang, Chen, Xiong, and Wang (2021)
5-Career Development	Interact with the employees to understand their career aspirations (through Q and A), and recommend opportunities, skills and corresponding training within the organization to develop the skills, help understand how the tasks, roles and job descriptions have changed over the years, and will change. Personalized recommendation on career path, by mapping career aspirations to specific skills and corresponding training/learning content to harness those skills, showing a pre-training and post-training skills map, maximizing their potential to perform and feel motivated.	Braganza, Chen, Canhoto, and Sap (2021)
6-Employee Performance Appraisal	Predict the performance of the employee based on the information available and new information provided before the appraisal and gathering information from other sources. Compare the performance of the employee to the set objectives. Provide recommendations to the manager based on the prediction and comparison (e.g. skills gap, new skills acquired, opportunities within the team and across the organisation, performance bonuses, promotion). Provide similar recommendations to the employee.	Krekel, Ward, and De Neve (2019), Smith (2019)
7-Compensation packages	Consider several heuristics such as, demand of the skills and expertise in the market and the market rate, current and past performance of the employee, relevance and importance of the skills and expertise for the organization, its competitiveness, productivity and dynamism. Therefore, making data-driven smart pay compensation.	Zehir, Karaboğa, and Başar (2020)
8-Employee Skills development	Recommend an automatic skills map for the employee, considering input from the employee, manager and considering job role, past learning history, business team. The map will bring together and organize training content for the employee, and show the value offered by the training. For HR managers/personnel, optimize administrative tasks related to capturing, processing and summarizing learning and training activities of the learners (engagement and interactions), to model employee engagement, learning needs and facilitate managers to make data-driven strategies.	Bughin et al. (2018), Jaiswal et al., 2021
9-Employee attrition detection	Predict the probability of an employee leaving the organisation using the available data drawn from employee profile, activities and appraisal, and historic dataset of employees who have worked/currently working in the organisation. Leveraging the power of explainable machine learning models, the decision makers can identify factors contributing to employee turnover and manage employee expectation by developing suitable strategies to retain employees.	Sabbineni (2020), Shankar, Rajanikanth, Sivaramaraju, and Murthy (2018)
10-Workforce management Analytics	AI can collect information about employee behavior, team practices and that of the department, to automatically detect mental health, well-being and presenteeism issues within a department. Providing information about engagement of employees within a team by aggregating and analyzing internal social media posts, to help understand social cohesion within teams, across teams, and support strategic workforce planning, to help increase employee motivation and engagement.	Margherita, 2021
11-HR Budget and resource allocation	AI can process all the quantitative and qualitative information obtained from all the available sources (internal and external market demands, competitors), additionally	Ahmed (2018), Tambe et al., 2019

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Context	AI application	Selected References
	take the business priorities of the organisation as input, to provide recommendations and explain them, in the context of budget allocation (for each priority and department), to help allocate, manage, track spending, without reducing employees and their services, in an efficient manner, and identify new priorities.	

Appendix B. Topics in the review

Sr. No	Topics	Citations
T1	AI and workforce analytics	Margherita, 2021
T2	AI and value for employee	Lichtenthaler (2019), Wang, Zhang, & Guo, 2021
T3	AI and value for organization	Burgess (2017), Fontaine et al. (2019)
T4	AI and achieving sustainability development goals	Di Vaio, Palladino, Hassan, and Escobar (2020), Cubric, 2020, Macke and Genari, 2019
T5	AI and organizational resilience	Arslan, Cooper, Khan, Golgeci, and Ali (2021)
T6	Drivers and barriers to AI adoption	Tariq, Poulin, and Abonamah (2021), Alsheibani, Cheung, and Messom (2019)
T7	AI Trust/transparency	Schmidt et al. (2020)
T8	AI employee wellbeing	Krekel et al. (2019)
T9	AI skills and knowledge [for workforce]	Bughin et al. (2018)
T10	AI socialization [teammate]	Seeber et al. (2020), Makarius et al., 2020
T11	AI new jobs+ green jobs	Rutkowska and Sulich (2020)
T12	AI and organizational agility	Saha, Gregar, and Saha (2017), Tallon, Queiroz, Coltman, and Sharma (2019)
T13	AI and organizational change management	Pumplun et al., 2019, Ransbotham et al., 2017
T14	AI in organizational decision-making	Araujo, Helberger, Kruikemeier, and De Vreese (2020)
T15	Different types of intelligences required in HRM jobs/processes	Haenlein & Kaplan, 2019; Daugherty et al., 2019
T16	HRM theory related to enhancing AI skills among employees within organizations	Jarrahi (2018), Kshetri (2021), Johnson, Stone, & Lukaszewski, 2020; Malik et al. (2020)
T17	AI and employee performance + business productivity	Damioli, Van Roy, and Vertesy (2021), Krekel et al. (2019),
T18	AI and organizational leadership	Iansiti and Lakhani (2020), Saha et al. (2017)

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