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Advancing Urban Waste Management Using Industry 5.0 Principles: A Novel Smart Bin

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***Abstract*—Smart bins represent a fundamental pillar of sustainability within the paradigm of Industry 5.0, revolutionizing waste management practices through advanced technological integration, by playing a crucial role in optimizing waste management through the integration of Internet of Things (IoT) capabilities, advanced sensory, and actuation modules. This paper investigates the pivotal role of smart bins through a comprehensive analysis of prevailing commercial solutions that reveals their present characteristics and limitations. By discerning and emphasizing notable drawbacks in existing products, a novel smart bin concept design is proposed that extends current capabilities through a synergistic combination of advanced sensing, automation, and data analytics. This innovative approach targets identified gaps, adopting a high-level holistic strategy to enhance efficiency in technology-driven urban waste management practices. Through this research, a contribution is made to the ongoing discourse on innovative solutions for sustainable urban development, emphasizing the transformative potential of intelligent waste management systems.**

***Index Terms*—smart bins, IoT, sensors, smart cities, automation**

I. Introduction

Urbanization and population growth invariably drive increased waste production in modern societies [1], [2]. Particularly in economically thriving cities, where production rates have reached unprecedented levels, the greater diversity of products and services, results in more challenging management, treatment, and disposal of larger volumes of waste [3]. Recent trends in rapid urbanization and industrialization have significantly contributed to this surge in refuse production, posing challenges for disposal and treatment that current practices struggle to address [4]. Insufficient waste management infrastructure, sub-optimal collection systems, and limited recycling facilities exacerbate the problem, leading to improper disposal practices such as open burning and illegal dumping, not only risking disease outbreaks due to the breeding of pathogens but also contributing to soil and water contamination from hazardous chemicals, posing long-term health risks [5], [6].

In the sphere of sustainability, a key component of Industry 5.0, technology-enabled smart bins have been developed to address the limitations of traditional waste management methods [7]. Industry 5.0 represents a paradigm shift in manufacturing, emphasizing the harmonious collaboration between humans and machines to achieve higher levels of productivity, efficiency, and sustainability. In essence, Industry 5.0 seeks to integrate advanced technologies with human ingenuity, leveraging automation while preserving the essential role of human expertise and creativity. Smart bins align with Industry 5.0 principles by embodying this collaboration through innovative design and functionality [8]. These advanced waste containers incorporate a mix of technologies, including sensors, data analytics, and automation, to transform the way waste is managed. Smart bins allow for the real-time tracking of waste quantities, optimization of collection routes and schedules, and the encouragement of effective garbage disposal practices. Additionally, the integration of robotics and diverse sensor and actuator arrays enables the immediate separation of materials, presenting a forward-looking solution to waste management challenges [9]. By leveraging advanced technology and data-driven approaches, these systems can operate more sustainably as well, minimizing resource wastage and environmental impact [10].

Despite the potential benefits, the progress and widespread acceptance of smart bins in modern societies remain limited. The instances observed often demonstrate only rudimentary functionalities, featuring too few sensors and capabilities. Notably, when it comes to waste sorting, the existing solutions are scarce, and the sorting capabilities they provide are either entirely reliant on manual intervention or are severely restricted in their automated functionalities. This paper endeavors to delve into the conceptual framework and attributes of smart

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bins within academic research, delineate the state-of-the-art (SotA), and pinpoint discernible gaps. In this context, a market analysis is conducted to identify the prevailing commercially available solutions. By synthesizing these findings, a novel smart bin design is introduced that combines pertinent technologies, aiming to comprehensively address identified gaps and drawbacks.

II. Relevant Research

In an attempt to comprehensively chart academic research on smart bins, several reviews have been published. Sosunova and J. Porras conducted an extensive and well-structured study focused on city-level solid waste management (SWM) through a systematic literature review [11]. The primary objective of the review was to create a holistic understanding of city-level SWM practices, including an exploration of smart bins. With a robust dataset and an analysis of over 170 relevant literature sources, the study efficiently extracted information on the presence of hardware in smart garbage bins. This meticulous approach facilitated a thorough mapping of various sensors and actuators employed in existing applications.

Ayodeji Noiki *et al.* in 2021, explored the potential of smart bins to enhance urban waste management in response to the escalating urbanization trend, which has led to a significant surge in waste generation in modern cities [12]. The study comprehensively examined over 25 identified cases of smart bins, categorized into several distinct groups. The review recognized numerous improvements and innovations in the field, indicating promising results. The study did identify a bottleneck in the wide application of smart bin technologies, resulting in relatively low adoption rates, highlighting that the implementation costs of smart bins remain high. Additionally, the review primarily emphasized IoT-enabled smart bins with data transfer capabilities and did not elaborate on waste separation capabilities and the reasons behind the scarcity of relevant cases in this area, akin to previous studies. Exploring this aspect further would enhance the completeness of the study and provide valuable insights into potential advancements in waste separation technologies.

In 2021, Sirsat and Bardekar conducted a study akin to the aforementioned one, albeit with a narrower scope, concentrating on 15 notable cases [13]. Similar to the prior research, this review also displayed a predominant focus on IoT-enabled solutions. The study articulated a clear acknowledgment of the potential for improvement in the realm of smart bins, posed inquiries regarding existing solutions for waste classification to enhance recycling, and offered insights into system costs.

In their relevant work, the authors of this present study delve into an extensive examination of nearly 80 cases drawn from over 1400 published papers, with a predominant focus on smart bins equipped with waste separation capabilities [14]. Research findings, presented as a journal review paper, currently under revision, target the development of a holistic picture of the state of the art regarding research and development on smart bins and underscore the scarcity of high-level solutions within academia pertaining to waste sorting functionalities. This work aims to offer valuable insights that complement existing reviews and contribute to a deeper understanding of waste management strategies.

In conclusion, the examination of related academic work has significantly contributed to gaining a comprehensive understanding of the state of the art of smart bins, particularly in terms of IoT connectivity, smart functionalities, and sensor integration. Notably, the focus has been on live monitoring of fill levels and waste conditions. However, it is essential to acknowledge that none of the mentioned cases were identified as production-ready, an expected outcome given that many advancements in this domain result beyond academia when they enter the market. As the next step, engaging in market research and analysis becomes imperative to identify and evaluate commercially available smart bins, discerning their functionalities. This approach is pivotal to establishing a more complete and practical picture of the current trends and limitations in the landscape of smart bin technology.

III. Market Analysis of Smart Bins

A novel market for smart bins in urban waste management has been identified. Upon closer examination, 7 different commercial products have been distinguished and are depicted in Fig.1:

1) *BigBelly SC5.5* is a smart bin developed by the Boston-based original equipment manufacturer (OEM), BigBelly [15], serving as a waste container for outdoor urban environments. It facilitates manual sorting by the user by placing containers adjacent, each for specific types of trash. Features onboard diagnostics, fill level sensing, and an optional solar-powered compactor to enhance its overall volume capacity by automatically compressing deposited items.
2) *Binwise* is provided by the Atlanta-based company Conure and is also designed for outdoor placement in urban settings [16]. This intelligent bin is equipped with ultrasonic proximity sensors that allow for real-time fill-level monitoring. Its functionalities further include IoT connectivity for the generation of alert messages for collection and maintenance crews when the container is reaching capacity, aiming for the optimization of waste collection scheduling.
3) *Smart City Separation Station 3 (SCSS3)* is a smart waste disposal unit from the Czech Republic-based OEM, Binology L.L.C. [17]. It features a multiple-bin rack for manual recyclable separation by the users, extendable to up to 9 individual containers to adapt to different separation scenarios. It incorporates IoT connectivity via GPS and GSM with cloud software. Moreover, this product includes ultrasonic fill-level monitoring, solar-powered compaction modules, and air quality sensing for monitoring waste deterioration.
4) *Garby* is a product developed by the Netherlands-based startup, Plaex Technologies in Enschede [18]. *Garby* serves as a smart bin, mainly intended for interior spaces, such as offices. It employs a vision-based smart

TABLE I
SUMMARIZED FEATURES OF THE AVAILABLE SMART BINS.

Product	**Bigbelly SC5.5**	**Binwise**	**Binology SCSS3**	**Garby**	**Terra Public Can**	**Bin-e**	**Trashbot**
Environment	Outdoors	Outdoors	Outdoors	Indoors	Outdoors	Indoors	Indoors
Sensing	Y	Y	Y	Y	Y	Y	Y
Fill level	Y	Y	Y	Y	Y	Y	N
Weight	N	N	N	N	N	N	N
Gas	N	N	N	N	Y	N	N
Environment	N	N	Y	N	Y	N	N
RFID	N	N	N	N	Y	N	N
Vision	N	N	N	N	N	Y	Y
IoT	Y	Y	Y	Y	Y	Y	Y
GPS	Y	Y	Y	Y	Y	Y	Not referred
GSM	N	N	Y	N	N	N	N
Other features	N	N	Deodorization, Sterilization	N	Safety lock	N	N
Actuation	Compaction	N	Compaction	N	Compaction	Waste routing, Compaction	Robot-based sorter
Solar powered	Y	N	Y	N	Y	N	N
Waste sorting	Y	N	Y	Y	Y	Y	Y
Manual sorting	Y	N	Y	N	Y	N	N
Automated sorting	N	N	N	Y	N	Y	Y
Single item	N	N	N	N	N	Y	Y
Multiple items	N	N	N	N	N	N	N

classifier for single-item automatic sorting. It also uploads data on deposited articles to an online dashboard aimed at tracking their overall impact on sustainability.

5) *Terra Public Can* was created and commercialized by the Croatia-based company Include d.o.o. [19]. It is an outdoor deployment smart bin. It assists in manual sorting through indication decals on the containers' outer casing. *Terra Public Can* is solar-powered, it incorporates fill-level sensing, a pressure, humidity, and temperature (PHT) sensor, GPS, server communication, and an RFID lock. An optional compaction feature is available to increase its overall volume capacity.
6) *Bin-e* developed by the Poland-based company Bine z.o.o [20], is a device targeting smart recycling for indoor locations. *Bin-e* features a 4-bin configuration and individual item manual deposition on a single entry point. Deposited items go through artificial intelligence (AI) based visual object recognition for automated sorting of metals, paper, and plastic. The system further includes fill-level sensors, compaction mechanisms for plastic and papers, and real-time cloud data management.
7) *Trashbot*, created by the USA-based OEM Clean-Robotics Inc., is a waste sorting solution mainly for interior spaces. *Trashbot* is equipped with an AI vision-based classifier and a robotic actuator for waste routing [21]. The user deposits a single item on the designated entry orifice and following its classification the device guides the item to its corresponding container robotically. It features cloud connectivity and integrated data analytics.

A more analytical depiction for each product's capabilities is presented in Table I.

IV. Proposed Novel Smart Bin Concept

Following the analysis of existing solutions in the market and insights from related academic work, a novel intelligent bin concept is proposed. This concept features a single IoT-enabled device with multiple internal compartments (Fig. 2). The process begins with mixed trash being inserted through the entry point and entering a buffer, where material flow is controlled via a regulating opening. The waste is then systematically deposited onto a conveyor belt with limited width, ensuring a linear formation.

In this setup, the waste input is transported along a conveyor belt. During this process, a series of inductive and capacitive proximity sensors are used to discern specific composition traits, mainly the identification of metal or wet components. Additionally, a Fourier Transform Infrared (FTIR) module is employed to detect plastics. Items exhibiting these specific traits are deflected sideways by linear actuators, directing them into dedicated individual buckets. The remaining items advance on the conveyor where they undergo visual inspection facilitated by a camera module coupled with AI capabilities and access to open trash databases, as well as an appropriate lighting source which is instrumental for precise identification [22]. This inspection enables the detection of recognizable objects such as bottles, pieces of paper, or cardboard, and subsequently, these items are further sorted into separate containers. Finally, the residual waste that does not meet any of the specified criteria is directed into a general waste bucket.

Load cells are strategically positioned beneath the metal and general waste containers to detect any weight increase, as these buckets are more likely to receive denser items. To effectively monitor the trash levels in each container, fill level sensing is integrated via ultrasound sensors, positioned over each compartment. Furthermore, to enhance the buckets'

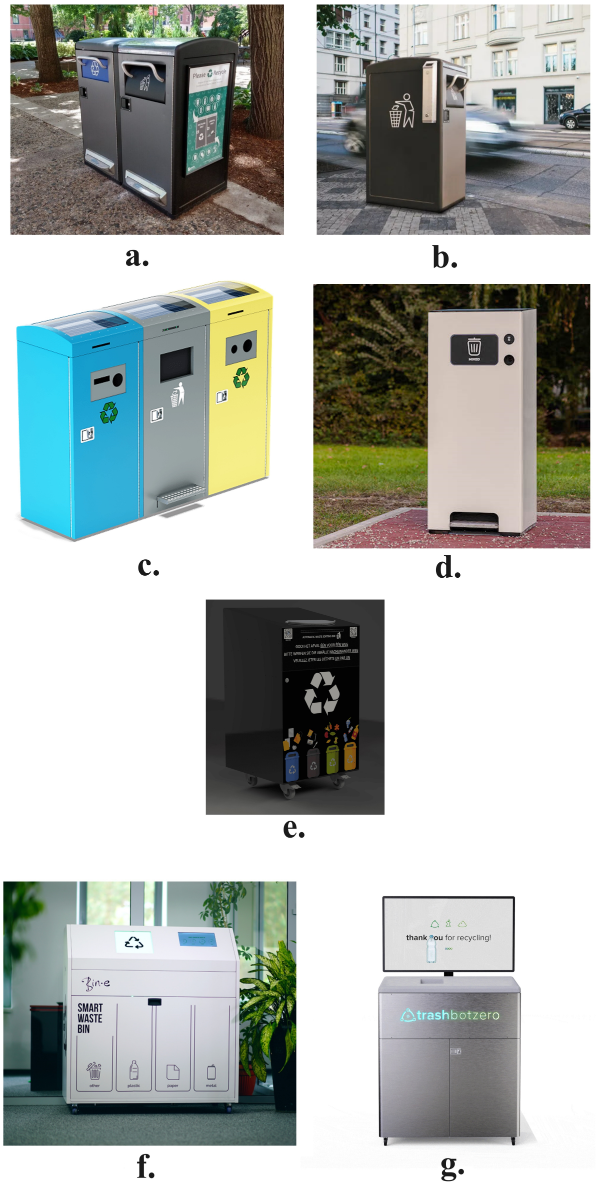

Fig. 1. Examined commercial smart bins indicative images. a)BigBelly SC5.5, b) Binwise, c) Binology SCSS3, d) Terra Public Can d) Garby, e) Bin-e, f) Trashbot

capacity, compaction mechanisms can also be incorporated over certain compartments, exerting pressure on the deposited contents and reducing their overall volume. For comprehensive monitoring, a BME680 sensor is included to track temperature, humidity, and air quality inside the bin.

The proposed concept follows a modular approach, allowing for customization by adjusting the conveyor's length and the number of buckets to accommodate diverse waste management scenarios. Depending on specific requirements, the type of sensors can be flexibly tailored as well. To ensure efficient waste management, all buckets are designed for easy removal by collection crews. Additionally, data collected from the integrated sensors is transmitted via WIFI for further analysis. A summary of all sub-systems included in this concept is

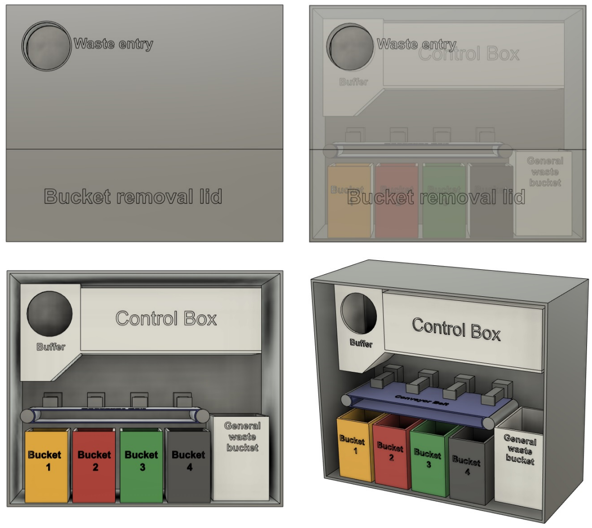

Fig. 2. Concept proposal for a smart bin with integrated waste separation capabilities

TABLE II
PROPOSED SMART BIN CONCEPT TABLE OF INDICATIVE INTEGRATED FEATURES.

#	Feature	Description	Category
1	Waste entry buffer	Initial compartment for mixed waste.	Structure
2	Buckets	Multiple buckets for waste sorting.	Structure
3	Controller	Electronics and controller board compartment	Structure
4	Ultrasound sensor	Fill level sensing	Sensing
5	BME680 sensor	Environment and air quality monitoring	Sensing
6	Inductive sensor	Metal detection	Sensing
7	Capacitive sensor	Wet waste detection	Sensing
8	FTIR sensor	Plastics identification	Sensing
9	RGB Camera	Object recognition	Sensing
10	Load cell	Bin Weight monitoring	Sensing
11	Conveyor belt	Waste routing (for classification)	Actuation
12	Linear actuator	Waste routing (deposition to buckets)	Actuation
13	Automated lid	Contactless operation	Actuation
14	Buffer flow regulator	Motorized opening at the bottom of the buffer for controlled material flow.	Actuation
15	Compactor press	Waste compaction for increased capacity	Actuation
16	AI	Optical Waste classification.	Function
17	IoT	Data transfer	Function

presented concisely in Table II. In the 'Category' row, the modules are classified into four distinct classes. 'Structure' encompasses the structural building blocks comprising the main body of the smart bin, including the frame and the control board. 'Sensing' and 'Actuation' categories pertain to modules dedicated to sensing and actuation functionalities respectively.

'Function' serves as an additional category reserved for hardware related to AI and connectivity modules.

The proposed concept presents several advantages over existing commercial solutions. Firstly, it supports multiple-waste entry, eliminating the need for inputting items one at a time. This functionality is further enhanced by the sophisticated waste routing system, integrating a conveyor-based circulation mechanism and a robot-based actuation system to sort various types of waste into individual containers. Additionally, the comprehensive array of sensors and connectivity modules is selected to cover the entire spectrum of sensing solutions encountered in commercial solutions, such as fill-level sensing, weight and environment conditions monitoring, while offering additional functionalities in terms of composition identification, through the use of metal and plastic detection, using inductive and FTIR sensors respectively. Lastly, the design's modularity enables easy reconfiguration of the bin to accommodate changes in material recovery needs and overall waste collection and separation requirements. This is achieved through reprogramming of the classifier and the array of buckets, ensuring adaptability.

V. Discussion

The identified commercial solutions demonstrate alignment with established trends in the literature. As indicated by the data presented in Table I, sensing functionalities prominently include fill-level sensing, with nearly all commercial smart bins (86%) incorporating this feature. In that realm, the Terra Public Can specifically stands out by offering Gas and Environment sensing, along with an RFID reader for automatic locking. Environmental sensing is also encountered on the SCSS3 in the form of air quality sensing to monitor the degradation of deposited organic waste. Additionally, computer vision is employed in three distinct instances (Garby, Bin-e, and Trashbot) for sorting purposes. No other forms of sensing, such as Weight monitoring, humidity detection, or composition-based identification methods were detected.

In terms of connectivity, all identified products are equipped with IoT functionalities, primarily for collection scheduling or data analysis of deposited waste. GPS connectivity is mentioned in nearly all cases (86%), with the exception of Trashbot, which did not specify the utilized technology. Notably, only one product (Binology SCSS3) refers to the utilization of GSM communication for data transfer.

Considering actuation, all but one product (Binwise) indicate a form of actuation (86%). Four out of the seven cases feature automatic compaction capabilities (57%), while one device exhibits automatic locking. Three out of seven present some form of mechanized waste routing. Within the context of waste sorting, only one bin does not mention waste sorting in any form (Binwise). Among the other six products, four incorporate manual sorting by the users, facilitated via external annotations and multiple individual containers. Two smart bin instances (Bin-e and Trashbot) provide automated sorting capabilities, albeit limited to one item at a time and designed for indoor use in workspaces and offices.

Finally, an interesting common feature among several products (43%) is the integration of solar power collection technology. The proposed concept aims to comprehensively address the identified shortcomings in smart bin functionalities. Sensing forms a crucial aspect, with fill-level monitoring serving as the baseline. To enhance accuracy, weight monitoring is integrated to efficiently complement fill-level sensing, particularly for heavy waste that may occupy containers with reduced volume. Environmental sensing is introduced to monitor waste quality, enabling prioritized collection in instances of increased waste deterioration.

In terms of waste classification, the conceptualized bin features multiple internal individual containers and an automated sorting mechanism. This design supports efficient waste segregation, a critical element in modern societies fostering recycling, material recovery, and circularity. The optimization of waste classification involves a combination of visual inspection and composition identification. The proposed approach utilizes AI-driven data fusion, incorporating machine vision for overall assessment, inductive proximity sensing for metal identification, capacitive sensors to locate wet waste, and an integrated FTIR sensor module for discerning specific plastics. To facilitate circulation within the system, a mechanism is introduced, consisting of a controlled flow buffer, a conveyor belt, and a series of mechanical linear side diverters. This combination ensures a regulated item flow, efficient categorization, and robust separation into the designated containers. The integrated design of sensing, classification, and circulation in the proposed concept addresses key limitations identified in current smart bin solutions, presenting a holistic and advanced approach to waste management.

VI. Conclusion

In conclusion, an investigation aimed to define the state of the art in smart bins was conducted by examining relevant research and conducting market analysis. The findings revealed that smart bins represent a novel and evolving field, with limited highly developed examples in current research. The market analysis identified seven distinct commercially available solutions, providing valuable insights into the existing landscape. The cumulative analysis resulted in a comprehensive understanding of the capabilities of technology-enabled waste bins. Leveraging this knowledge, a novel smart bin concept is proposed, addressing both existing and non-encountered functionalities. The proposed concept capitalizes on a synergistic combination of sensing subsystems to enhance the bin's overall capabilities. Additionally, it introduces a dedicated system for automated waste classification, circulation, and physical separation into individual containers. The envisioned smart bin concept aspires to transcend conventional functionalities, resembling a miniaturized material recovery facility. This innovative approach positions the smart bin as a localized solution deployed directly in neighborhoods. The ultimate goal is to contribute to the optimization of municipal waste management practices, marking a significant step towards more efficient and sustainable waste handling in urban areas.

The next steps of this work primarily involve further developing and refining the proposed concept, transitioning into a working smart bin prototype. The prototype will subsequently undergo deployment for experimentation and performance validation under real operating conditions, to analyze its performance and inform further iterations and potential enhancements.

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Artificial Intelligence and Robotic Technologies in Tourism and Hospitality Industry

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ARTIFICIAL INTELLIGENCE AND ROBOTIC TECHNOLOGIES IN TOURISM AND HOSPITALITY INDUSTRY

Reha KILIÇHAN[a] Mustafa YILMAZ[b]

Abstract

Artificial intelligence applications and robotic technologies, which are rapidly spreading and widely used throughout the world, are discussed by different disciplines in the literature. The field of tourism draws attention as one of the disciplines in which studies on these issues have been carried out in recent years. In this context, robots come to the fore in the application areas of the tourism sector. However, it is known that there are many artificial intelligence applications that are becoming widespread or likely to become widespread day by day in the tourism sector. From this point of view, in this conceptual study, firstly artificial intelligence applications and robotic technologies were evaluated, the development of these technologies was revealed, then the current technologies used in the tourism and hospitality industry were examined, and as a result, the future of these technologies in the tourism and hospitality industry was discussed. In this context, it can be said that this study, in which the current situation is revealed and sector-experienced writers make inferences for the future, is an important study that can contribute to the literature and industry practitioners.
Keywords: Artificial Intelligence, AI, Robotic Technologies, Tourism

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TURİZM VE AĞIRLAMA ENDÜSTRİSİNDE YAPAY ZEKÂ VE ROBOTİK TEKNOLOJİLER

Öz

Dünya genelinde hızla yayılan ve yaygın olarak kullanılmaya başlanan yapay zekâ uygulamaları ile robotik teknolojiler konularının literatürde farklı disiplinlerce ele alındığı görülmektedir. Turizm alanı da bu konularda son yıllarda çalışmaların gerçekleştirildiği disiplinlerden biri olarak dikkat çekmektedir. Bu bağlamda, turizm sektörünün uygulama alanlarında robotlar ön plana çıkmaktadır. Ancak turizm sektöründe her geçen gün kullanımı giderek yaygınlaşan veya yaygınlaşma ihtimali olan pek çok yapay zekâ uygulamalarının da olduğu bilinmektedir. Bu noktadan hareketle, kavramsal bir çalışma özelliği taşıyan bu çalışmada literatürden hareketle, öncelikle yapay zekâ uygulamaları ve robotik teknolojiler değerlendirilmiş, bu teknolojilerinin gelişimi ortaya konulmuş, ardından turizm ve ağırlama endüstrisinde kullanılan güncel teknolojiler irdelenmiş ve sonuç olarak bu teknolojilerin turizm ve ağırlama endüstrisindeki geleceği tartışılmıştır. Bu bağlamda, mevcut durumun ortaya konulduğu ve sektör deneyimli yazarların geleceğe

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dönük çıkarımlarda bulunduğu bu çalışmanın literatüre ve sektör uygulayıcılarına katkılar sağlayabilecek nitelikte önemli bir çalışma olduğu söylenebilir.

Anahtar Kelimeler: Yapay Zekâ, YZ, Robotik Teknolojiler, Turizm

Introduction

The tourism and hospitality industry is human- and service-oriented by nature. Hence, it aims to ensure consumers develop positive perceptions of the quality of the services provided by businesses serving in this field, i.e., to achieve their satisfaction and loyalty. In this context, providing quality service in tourism becomes more and more prominent every day. Businesses desiring to provide quality service also carry out studies to satisfy consumers' demands and needs, and realize plans and policies in light of current developments. In this industry, where services have always been oriented to people, it is observed that businesses have been following technological developments in recent years, and trying to adapt their services to the demands of the age as long as technological opportunities allow. Although they do not seem possible to replace humans entirely, robotic technologies become prominent in the tourism and hospitality industry, and the use of artificial intelligence applications in this industry draws attention. Although the use of such technologies, which have become widespread in almost every sector today, is partially criticized by some stakeholders of the tourism and hospitality industry, it is inevitable for businesses to follow, accept, and apply these technologies as a requirement of the age.

Even though the positive and adverse effects of artificial intelligence applications and robotic technologies are still contradictory on the service quality in the tourism and hospitality industry, which is a labor-intensive industry, they are known to be used mostly by businesses engaged in accommodation, food and beverage, travel, and transportation. In addition, the use of such technologies in physical areas, such as airports and museums, and tour guiding, should be underlined. It is noted that businesses serving in the tourism and hospitality industry have turned to artificial intelligence applications and invested in robotic technologies to improve their operations and provide higher quality services. Although it is not now possible for the mentioned businesses to realize all their services using these technologies, it is expected that the services will gradually focus on artificial intelligence and robotic technologies in the future as the technology acceptance levels of both businesses and consumers increase.

It is realized that the number of academic studies on robotic technologies and artificial intelligence applications is increasing day by day. Nevertheless, studies scrutinizing the future place and significance of artificial intelligence and robotic technologies used in the tourism and hospitality industry are somewhat limited. As a matter of fact, this study, written by academics with national and international sector experience in accommodation, food and beverage, and travel and transportation management, has taken a supportive and critical approach and made relevant evaluations about the future of the subject. From this point of view, the study is likely to not only contribute to the elimination of the lack of information in the literature but also suggest helpful information to practitioners with the help of the perspectives of the academics who know of the sector and consumer demands and needs. In this context, this study firstly evaluates the subject of artificial intelligence and robotic technologies, secondly examines the development of artificial intelligence technology, and then investigates the subject of current artificial intelligence applications in tourism and hospitality industry under the headings of robots, chatbots, facial recognition, language translators, optimization services and other AI applications. Finally, it makes several inferences on artificial intelligence and robotic technologies in the future of the tourism and hospitality industry.

A. ARTIFICIAL INTELLIGENCE AND ROBOTIC TECHNOLOGIES

One of the most remarkable consequences of the Fourth Industrial Revolution (Schwab, 2016), which came to the agenda for the first time in 2011 in a fair in Hannover, Germany, is that artificial intelligence and robotic technologies are no longer science fiction and are frequently used in the daily life. The definitions proposed for the concept of artificial intelligence lead to an interpretation that this technology is a sub-branch of computer engineering (Tussyadiah, 2020). Artificial intelligence is the field of computer science that studies how machines can act intelligently (Gil et al., 2020, p. 4). Artificial intelligence is a computer-based system with several features, such as problem-solving, storing something in memory, and understanding human language (Wang, 2004, p. 368). It is also defined as "the ability of a system to interpret external data correctly, learn from such data, and use these learnings to achieve certain goals and tasks through flexible adaptation" (Kaplan & Haenlein, 2019, p. 15). Definitions for the concept of artificial intelligence are generally divided into four separate categories: thinking humanly, thinking rationally, acting humanly, and acting rationally (Russell & Norvig, 2016, p. 2). Machines must have six features to act humanely: (a) natural language processing (for accessible communication), (b) knowledge representation (to store what it knows or hear in its memory), (c) automated reasoning (to use the information stored to answer questions and obtain new results), (d) machine learning (to adapt and predict new conditions), (e) computer vision (to detect objects), and (f) robotics (to move objects with itself) (Russell & Norvig, 2016, pp. 2-3).

International Federation of Robotics (IFR) indicates that robots are divided into industrial robots and service robots (International Federation of Robotics, 2020). According to ISO 8373: 2012, an industrial robot is "a robot that can be automatically controlled, reprogrammable, multipurpose, manipulator, programmable in three or more axes, which can be either fixed in place or mobile for use in industrial automation applications" (The International Organization for Standardization, 2012). In the same standard, a service robot is defined as "a robot that performs useful tasks for humans or equipment excluding industrial automation applications." Murphy et al. (2017, p. 106) uncover the features of industrial and service robots, as shown in Table 1. As shown in the table, not only do industrial robots have almost no mobility but their social interactions are also very low. It is predicted that industrial robots will grow at an average rate in the future. On the other hand, service robots are more mobile and socially interact with their environments than industrial robots. When the three types of robots are considered together, it can be emphasized that the degree of autonomy of personal service robots is higher than other robots, and that they have the most social interaction by entertaining people (Murphy et al., 2017, p. 107).

Table 1. Robot Types and Characteristics (Murphy et al., 2017, p. 106)

	Industrial	Professional Service	Personal Service
Existence	~ 50 years	~ 20 years	~ 20 years
Applications	Manufacturing	Remote areas, health care, aged care, deep water repairs, mine clearing	Home, recreation; e.g. as human companions
Social Interaction	Little to none	Some	Moderate
Mobility	Little to none	Some	Moderate
Autonomy	Semi-autonomous: programming	Semi to somewhat autonomous: teleoperation and programming	Somewhat autonomous: programming and artificial intelligence
Hospitality & Tourism Examples	Food preparation	Room cleaning, heritage preservation, telepresence robots at conferences, medical tourism	Concierge robots in hotels and visitor centers, museum guides, airport and destination greeters
Projected Growth	Moderate	Strong	Very strong

It is known that robots used in the tourism and hospitality industry generally emerge as professional or personal service robots. These robots are offered to consumers in the industry and provide great convenience to a business in meeting its customers' personal needs. Although the use of robots in the tourism and hospitality industry is limited today, the robust growth in the robotic field foreseen in the coming years can be interpreted as the use of these robots will gradually increase. Thus, it seems possible for tourism businesses to gain some benefits, such as reducing costs, gaining a competitive advantage, and increasing guest satisfaction.

B. DEVELOPMENT OF ARTIFICIAL INTELLIGENCE TECHNOLOGY

The history of the studies in the field of artificial intelligence is not very old. Milestones regarding the historical development of artificial intelligence are listed in Table 2 in chronological order. The historical development of artificial intelligence is examined in three phases: inception (infancy), industrialization, and explosion, according to the classification made by the CAICT (2018). In this context, the first essential development in this field is the Turing Test developed by Alan Turing. In his article published in Mind, Turing (1950) sought an answer to the question “Can machines think?” and developed the Turing Test as a result of this work. Many researchers consider the research by Alan Turing and the Turing Test the beginning of artificial intelligence research (Ritter, 2019; Saygin et al., 2000, p. 463). John McCarthy first introduced the concept of artificial intelligence in a two-month workshop held at Dartmond College in the Summer of 1956, and he defined artificial intelligence as “the science and engineering of making intelligent machines, especially intelligent computer programs” (McCarthy, 2007, p. 2). Research in the field started to gain momentum with this workshop. A group of 10 professors, including John McCarthy of Dartmouth College, Allen Newell and Herbert Simon of CMU, Trenchard More of Princeton, Arthur Samuel of IBM, and Ray Solomonoff and Oliver Selfridge of MIT, and their students participated in this workshop, and the following proposal was presented as a conclusion of the workshop (Russell & Norvig, 2016, p. 17):

> “… The study is to proceed on the basis of the conjecture that every aspect of learning or any other feature of intelligence can, in principle, be so precisely described that a machine can be made to simulate it. An attempt will be made to find how to make machines use language, form abstractions and concepts, solve kinds of problems now reserved for humans, and improve themselves. We think that a significant advance

can be made in one or more of these problems if a carefully selected group of scientists work on it together for a summer."

Table 2. Milestones of Artificial Intelligence Development (Adapted from Berliner & Ebeling, 1990, p. 105; Buchanan et al., 1969; CAICT, 2018, pp. 4-5; McCorduck, 2004; Neapolitan & Jiang, 2018, pp. 2-4; Russel & Norvig, 2016, p. 26)

Stages	Year	Iconic Event
Inception (Infancy)	1950	Alan Turing developed an empirical test of artificial intelligence called The Turing Test. This test is an operational test; that is, it provides a concrete way to determine whether the entity is intelligent.
	1951	Marvin Minsky and Dean Edmonds built SNARC, the first neural network computer.
	1955-1956	Allen Newell and Herbert Simon developed a program called the Logic Theorist that was intended to mimic the problem-solving skills of a human being and is considered the first artificial intelligence program.
	1956	The Dartmouth Conference in the US gathered the first batch of researchers to determine the name and mission of AI, which was called the birth of AI.
	1957	Frank Rosenblatt, an experimental psychologist at Cornell University, implemented a neural network "perceptron".
	1965	DENDRAL was the first successful knowledge-intensive system and the first expert system: its expertise derived from large numbers of special-purpose rules. DENDRAL interpreted the output of a mass spectrometer (a type of instrument used to analyze the structure of organic chemical compounds) as accurately as expert chemists.
	1969	The International Federation of Artificial Intelligence was established and the first meeting was held in Seattle, Washington, US.
Industrialization	1980	Carnegie Mellon University designed an expert system called eXpert CONfigurer (XCON) for Digital Equipment Corperation (DEC), which was a huge success, and at that time it saved the enterprise USD 40 million each year.
	1982	Japan planned to invest USD 850 million to develop AI computers (the fifth-generation computers), aiming to create machines that can talk to people, translate languages, interpret images, and reason like humans.
	1986	Multi-layer neural networks and BLEU points (BP) back-propagation algorithms have emerged to improve the accuracy of automatic recognition.
	1988	The German Research Centre for Artificial Intelligence was established and is currently the world's largest non-profit AI research institution.
	1988	Judea Pearl's Probabilistic Reasoning in Intelligent Systems led to a new acceptance of probability and decision theory in AI.
	1988	HiTech program defeated former US Champion and Grandmaster Arnold S. Denker at the game of chess by a score of 3.5 - 0.5 in the AGS Challenge Match
	1997	Deep Blue, a chess-playing computer developed by IBM, defeated the world chess champion, a milestone event in the history of AI; under the influence of Moore's Law, computing performance began to increase dramatically.
Explosion	2000	Robot pets, smart toys, become commercially available; C. Breazeal creates Kismet, a robot that exhibits emotions
	2001	Berners-Lee et al., begin work on the Semantic Web, an international effort to bring about the global exchange of commercial, scientific and cultural data on the World Wide Web, using AI techniques of logic, inference, and action
	2006	Geoffrey Hinton proposed a training algorithm in "Science" based on Deep Belief Networks (DBN) that can use unsupervised learning, making deep learning continue to heat up in academia.
	2011	The IBM Watson system won at the US game show Jeopardy! against human players.
	2012	The deep learning algorithm became well-known after the ImageNet Challenge, and was thereby widely used.
	2016	AlphaGo developed by DeepMind defeated former World Go champion Lee Sedol.

Then, a project called DENDRAL was developed in 1965, and this project became the first successful knowledge-intensive system supported by artificial intelligence. DENDRAL had the ability to interpret results correctly, like an expert chemist. Following these developments, the International Federation of Artificial Intelligence was established in 1969, and artificial intelligence developed into a global research field. Increasing the investment budgets in this field in the United States and Japan since 1980 and the establishment of an artificial intelligence research center in Germany in 1988 - the world's largest artificial intelligence research institute - showed that the artificial intelligence studies came in the period of industrialization.

The most striking of the developments in artificial intelligence was that artificially intelligent computer programs defeated the world chess champions. For example, the HiTech program defeated Arnold Denker in 1988. Another example is the Deep Blue program, which was started to be developed by IBM in 1985. The program successfully defeated the world chess champion Garry Kasparov in 1997 (Chen, 2019). Increasing artificial intelligence research since the 2000s has made this field now booming. Data has been started to be generated by sensors and chips since this phase, and the development of artificial intelligence technology has gained momentum with big data. Artificial intelligence robots have been introduced to many sectors, and artificial intelligence has begun to be used in technologies, such as autonomous devices and smart machines. Considering the developments to date, it is among the facts obtained as a result of the research that artificial intelligence technology has started to take place in daily life practices and that the number of devices using artificial intelligence technology will gradually increase.

The relationship between artificial intelligence and industrial revolutions is shown in Figure 1. There was mechanical automation in the first industrial revolution. Then, specific transitions occurred from mechanization to widespread use of electrification in the second industrial revolution; from simulation to digitalization in the third industrial revolution; and from automation systems to intelligent systems with the fourth industrial revolution. Two far-reaching aspects of artificial intelligence are machine learning and deep learning algorithms, which make artificial intelligence technologies convenient for industries. Machine learning and deep learning can be expressed as the extensions of today's popular algorithms and symbolism, evolutionism, and connectionism theories given in the section “Progress” in Figure 1 (CAICT, 2018, p. 8), which reveals the importance of machine learning and deep learning in the field of artificial intelligence.

Machine learning, neural networks, and deep learning are clustered under the term artificial intelligence and are shown in Figure 2. Machine learning has been seen as a sub-branch of artificial intelligence since the 1950s and has evolved into some fields in the last few decades. On the other hand, deep learning has been used as a sub-branch of machine learning since 2006 (Alom et al., 2019, p. 2). Machine learning is a technology based on programming computers to optimize the performance of existing criteria with sample data or past data and help understand and solve many problems in vision, speech recognition, and robotic technologies (Alpaydin, 2014, p. 3).

Figure 1. AI Setting off a New Wave of Technological Development (CAICT, 2018, p. 8)

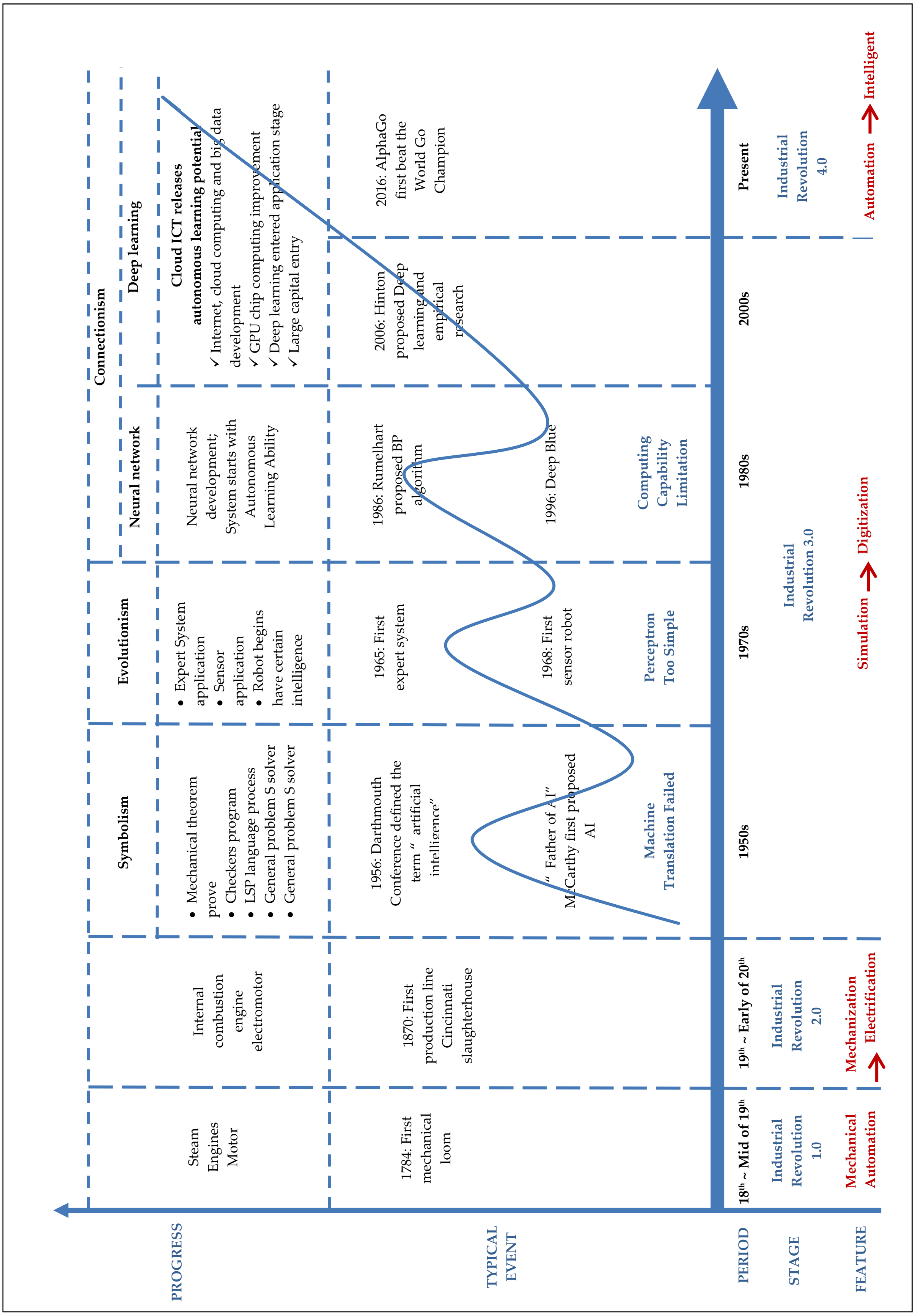

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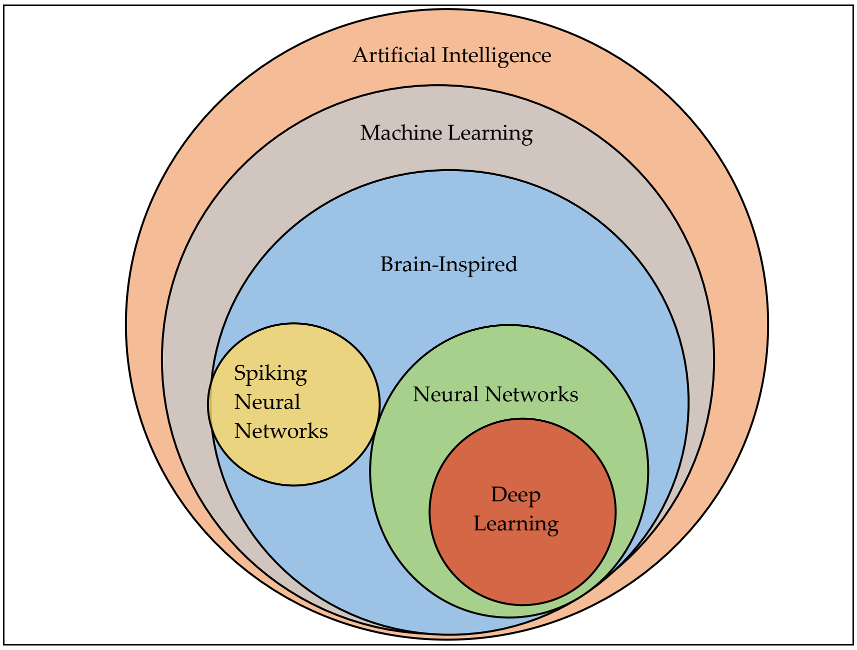
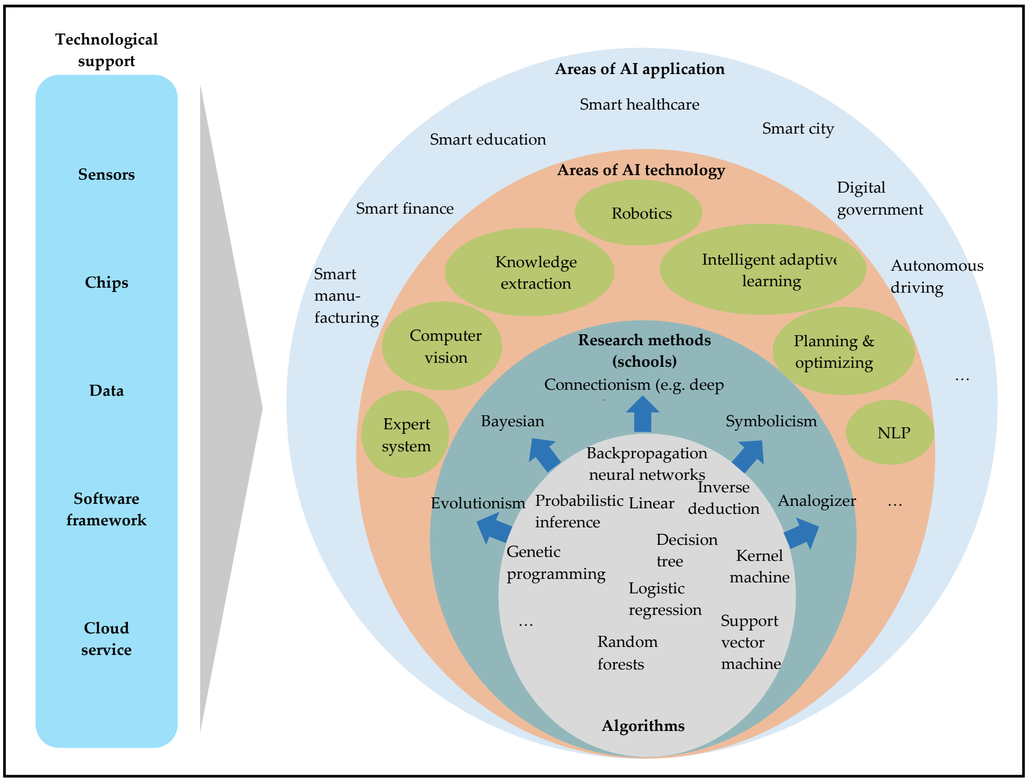
Figure 2. The Taxonomy of AI (Alom et al., 2019, p. 2)



There are three types of machine learning algorithms: supervised learning, unsupervised learning, and reinforcement learning; it is divided into two as static learning and dynamic learning by time (Joshi, 2020). Supervised learning includes learning functions by performing operations on a training set (Neapolitan & Jiang, 2018, p. 89) and includes methods and techniques, such as linear regression, logistic regression, decision trees, neural networks, and support vector machines (Rasmussen & Williams, 2006, p. 165). Unsupervised learning is a type of machine learning that aims to discover patterns in large data sets or to classify data into some categories without being clearly trained and to classify according to this distinction and includes cluster analysis and feature extraction (Wang, 2016). It also has methods, such as principal component analysis and auto-encoder (Hu et al., 2017). Reinforcement learning, on the other hand, is a learning technique based on receiving feedback from the environment (Joshi, 2020, p. 11) and used to understand the unknown environment (Alom et al., 2019, p. 3). It differs from supervised learning and unsupervised learning in that it focuses on goal-oriented learning through interaction (Sutton & Barto, 2018). In addition, the type of learning through data that is taken based on a single snapshot and does not change in time is called static learning, and the type of learning through continuously changing data over time is called dynamic learning. Reinforcement learning is considered dynamic learning due to the data that changes over time with interaction (Joshi, 2020, p. 11).

Figure 3. Illustration of all Levels of AI (Deloitte, 2018, p. 6)



Example areas where artificial intelligence applications are often used are given in Figure 3. The imperative factor for artificial intelligence is data. Artificial intelligence applications cannot make any movement, guidance, or prediction without data. Data, i.e., technical support, is transmitted to artificial intelligence applications through other technologies, such as sensors, chips, software, and cloud services. These transmitted data are processed in artificial intelligence applications and used in smart manufacturing, smart finance, smart education, smart healthcare, smart city, smart destination, digital governance, autonomous driving, etc. Artificial intelligence technologies using algorithms and various research methods emerge as technologies, such as expert systems, computer vision, knowledge extraction, robotics, intelligent adaptive learning, planning and optimizing, and Neuro-Linguistic Programming (NLP). It can be indicated that artificial intelligence technologies have primarily emerged as optimization and robotic technologies that increase the guest experience in the tourism and hospitality industry. They can also be used in this industry through joint areas, such as smart city, smart destination, digital governance, smart hotel, and smart education.

C. CURRENT ARTIFICIAL INTELLIGENCE APPLICATIONS IN THE TOURISM AND HOSPITALITY INDUSTRY

The use of artificial intelligence technologies in the tourism industry is gradually becoming popular. Tourism businesses now invest in these technologies to gain a competitive advantage and increase productivity. The use of artificial intelligence in these businesses mostly emerges as the use of service robots. Accordingly, this section examines the applications of artificial intelligence in tourism businesses, concrete examples of the use of such applications from the sector, and their significance in detail. In this context, this study refers to the classification made by Samala et al. (2020), and artificial intelligence technologies are classified in this study as robotic technologies, facial recognition technologies, chatbots, language translators, optimization services, and other artificial intelligence applications.

1. Robotic Technologies

Robotic technologies are the most common applications of artificial intelligence technologies in the tourism and hospitality industry. Robots come into prominence as piloted technologies. Their usage is becoming increasingly widespread, and they are seen as emerging technologies in the tourism and hospitality industry. In this context, below are the application examples of robotic technologies in the tourism and hospitality industry.

1.1. Robot Receptionist

The world's first robotic hotel is Henn-na Hotel in Japan. Humanoid robots welcome guests at the hotel, and these robot receptionists do their check-in (Tung & Au, 2018, p. 2685). Henn-na Hotel employs very functional transport robots in the front office department to accompany guests, carry their luggage, and provide reception services (Lewis-Kraus, 2016).

1.2. Robot Bellboy

A service robot called “Sacarino” serves as a robot bellboy for guests (Zalama et al., 2014). Sacarino provides information to guests about hotel facilities, activities around the hotel and the city (restaurant opening hours, restaurant menus, etc.), and video conferencing services, as well as calling a taxi, accompanying guests to the hotel restaurant or rooms, and searching information requested by the guests on the internet. It has a self-charging feature by connecting to its own station in the hotel lobby (Park, 2020, p. 3; Pinillos et al., 2016, p. 41; Zalama et al., 2014, p. 4). In addition, the world's first robotic arm-shaped suitcase carrier, called YOBOT, has been put into service at Yotel New York (Yotel New York, 2020).

1.3. Robot Concierge

Hilton has partnered with IBM on a robot named “Connie”, where the information it will provide to guests is powered by the Watson artificial intelligence application base. Connie is a humanoid robot concierge that provides information about the hotel and its destination to guests (Davis, 2016; Hilton Worldwide, 2016; Park, 2020, p. 3). Connie is able to interact with guests by responding to their questions about the services offered in the hotel and recommends the attractions around the hotel for guests. Connie acquires new information every time it interacts with guests and improves itself for potential questions that may be asked in the future since it is supported by artificial intelligence (Ivanov et al., 2017, p. 1506). In 2018, Italy's first robot concierge called "Robby Pepper," developed by Japan's Softbank Robotics and able to serve in Italian, English, and German languages, started to be used in a hotel located on the shore of Lake Garda in Italy (Barry, Pele, 2018). "Connie" and "Robby Pepper" provide guests with detailed information about the places to visit, activities to do, and the hotel based on the weather and the check-out dates of them (CRM Medya Turizm, 2020). Another robot concierge called "Mario" is used in the Ghent Marriott Hotel in Belgium (Chestler, 2016; ReviewPro, 2016).

1.4. Robot Bartender

A robot bartender can be in the form of a robotic arm or in a humanoid appearance (Tussyadiah et al., 2020). It has two robotic arms located in the bar's center under the bottles (Berezina et al., 2019, p. 205). It generally has the ability to perceive the guests as human beings, to receive and deliver their beverage orders (Giuliani et al., 2013, p. 263). On the cruise ship named "Quantum of the Seas", operated by Royal Caribbean, the robot bartender, which is the first bartender in cruise tourism in the world, takes the beverage orders of the passengers via the tablets in the bar, and passengers can watch the robotic arm while their orders are prepared. Since the robot is pre-programmed for the mixture amounts, it takes the right amount of the products required for the mixture and serves the beverages with ice and lemon to the guests (Sloan, 2014).

1.5. Delivery Robot/Robotic Butler

An example of a robotic butler/delivery robot can be encountered in the Aloft Hotels - brand of the Starwood hotel chain -, and the robot is used to deliver orders to the rooms instead of human employees (Crook, 2014; Markoff, 2014; Park, 2020, p. 3). Another example is a delivery robot named "Wally" at the Residence Inn Marriott LAX Hotel (Tung & Au, 2018, p. 2685). In addition, Hotel Jen in Tanglin employs two delivery robots, named "Jeno" and "Jena." They are located in the lobby area, dressed in uniform, and they depart for rooms at an average speed of 2.5 km, slower than a person's walking speed, and deliver guests' orders (Lin, 2017). These robots can roam around the hotel, use the elevator, call the room when they arrive at the guest's door, and deliver orders to the guest (Ivanov et al., 2017, p. 1506). In addition, if a guest requests something, such as a toothbrush or an extra towel, the hotel staff loads such requests to the order delivery robot, calls the room, and sends the orders to the guest's room (Crook, 2014).

1.6. Robot Chef

M Social Singapore Hotel introduced the robot chef named "Ausca" in 2017. It is stated that this robot chef can cook sunny side up and omelets and can improve itself by learning more different egg cooking techniques (Lin, 2017). Furthermore, there are also robot chefs that can cook sushi (Sushirobo.com, 2020), noodles named "Foxbot" (Elkins, 2015), a sausage named "BratWurst Bot" (Filloon, 2016), and burgers (Troitino, 2018).

1.7. Robot Waiter (Server)/Robot Busser

The use of robots as waiters in the service industry is an increasingly common practice. It is pointed out that restaurant owners look for robot waiters to assist in providing service to guests in cases where the staff cannot keep up with the orders or the number of waiters is limited (Cheong et al., 2016, p. 681). Robot waiters and robot bussers can assist restaurant staff when restaurants are busy; however, it is also stated that the overuse of robots may cause the dismissal of some employees (Ivanov & Webster, 2020, p. 1073). A robot in a red apron and holding a tray meets guests in a seafood restaurant called Rong Heng in Singapore; the orders of the guests are brought by two robots named "Lucy" and "Mary" with a stylish scarf around their necks (Ang, 2016).

1.8. Robot Housekeeper

Park Avenue Rochester Hotel is the first business hotel in Singapore to employ robots to deal with the hotel's affairs. The robot named "Robie" in this hotel helps housekeeping employees carry linens, garbage, large-volume items, and bulk products between floors. Robie can do the work of 3.5 full-time employees by itself thanks to its performance throughout the day, which provides cost savings to the business (Lin, 2017).

1.9. Robot Host/Hostess

Robots can also be used to encourage sales. Tanuki restaurant in Dubai utilizes a robot host to attract guests to the restaurant. The robot host can communicate with guests, give them discount coupons, and persuade guests to visit the restaurant (Ivanov & Webster, 2020, p. 1073). Robot hosts can be thought of as an alternative to human hosts for tech-savvy restaurants or the ones targeting young customers. Communicating with such robots can be a futuristic experience for tech-savvy customers, and they allow such customers to have fun during their visits to the restaurant (Berezina et al., 2019, p. 198).

1.10. Robot Guide

Robot guides are included in the "mobile guide and information robot" category in the classification made by the International Federation of Robotics and are the ones that provide information to people in museums and exhibition places (Yıldız, 2019, p. 170). Yamazaki et al. (2009) developed a robot guide to introduce the museum artifacts to the visitors and interact with them in the Ohara Art Museum in Kurashiki, Japan.

1.11. Drones

A drone is defined as "an aircraft without a pilot, controlled from the ground, used for taking photographs, dropping bombs, delivering goods, etc." (Oxford Learner's Dictionaries, 2020). Drones were first considered unmanned aerial vehicles used in military operations (Russel & Norvig, 2016, p. 1009). For example, the word drone was first used in the US Navy in 1935 (Clarke, 2014, p. 235). Later, drones have shown themselves in different industries for various purposes. There are also studies on the use of drones in order delivery in the tourism and hospitality industry (Hwang, Cho, & Kim, 2019; Hwang, Kim, & Kim, 2019; Hwang, Lee, & Kim, 2019; Hwang, Kim, & Kim, 2020). Other than order delivery, drones are used for video shooting for destination marketing (Stankov et al., 2019) and photographing to monitor visitors in areas such as archaeological sites (Donaire, Galí & Gulisova, 2020). In the food and beverage industry, drones serve as waiters in Timbre @ The Substation by carrying meals and beverages to customers (Millward, 2015). Domino's Pizza has delivered the first commercial drone pizza to a customer in Auckland, New Zealand (Lui, 2016). Since drones use electric power in order delivery, they contribute to the green image of food and beverage businesses in protecting the environment (Hwang & Kim, 2019).

2. Chatbots

A chatbot is a software program that enables users/consumers to communicate with the system using their native languages (Abu Shawar & Atwell, 2007, p. 29). It is one of the self-service technology applications and can also be named as "virtual agent" or "chatterbot." It can pop up in web pages or mobile applications of the businesses (Melián-González et al., 2019, pp. 1-2). In the same study, reviewing the comments on Tripadvisor, it is given that the guests of hotels, restaurants, and transportation and entertainment centers frequently use chatbots. Marriott International allows its guests to make their reservations for any of its 4,700 hotels via a chatbot on Facebook Messenger (Phaneuf, 2020).

3. Facial Recognition

Biometric technologies are based on using people's physical characteristics, such as eyes, iris, fingerprint, face, palm geometry, and voice. These technologies adopt the principle of shortening daily work processes and making people's lives easier by using their biometric data. Facial recognition technology is also among such biometric technologies. In the context of the tourism industry, consumers/users take advantage of such technologies. For example, passengers at Gatwick Airport in the UK do their own passport controls by scanning their face on a face recognition system (Ivanov & Webster, 2019, p. 16). Customers at Ufood Grill in Maryland can place their orders and make payments in less than 10 seconds using facial recognition technology (Marston, 2017). A kiosk, which serves on the basis of facial recognition technology at the KFC restaurant in Beijing, offers meals by gender, ages, and moods of the customers (Wu, 2017). Guests can perform their check-ins and check-outs very quickly using facial recognition technologies at Fairmont Singapore, Swissotel The Stamford Marcus Hanna (Rajagopal, 2019), and Marriott Hotels in China (Revfine, 2020). In China, Alibaba's FlyZoo Hotel uses facial recognition technology to enable its guests to select and book their rooms (Wolfe, 2019). Considering that the global face recognition technology market is USD 4.05 billion in 2017 and is expected to reach USD 7.76 billion by 2022 (Hristova, 2019), it is not prudent to state that using these technologies in the tourism and hospitality industry will gradually increase.

4. Language Translators

The key problem of a tourist when it goes abroad is related to the language barrier. Language translators are among the most critical technological software that helps a tourist to communicate with the local people and participate in tourism activities in the relevant destination by using the local language. Today, several programs help solve the foreign language problem, and the well-known of these is "Google Translate." Google translate allows a tourist who travels to a country and does not know the language to communicate with the local people in their own language. The tourist translates the sentence in its own language through the Google Translate program to the local language, or the tourist understands what others mean by translating the sentence spoken by them into its own language via the program; thus, a more accessible and more understandable communication can be established. Apart from Google Translate, applications, such as Microsoft Translate (Microsoft, 2020), SayHi (an Amazon company) (SayHi, 2020), and iTranslate Translator (an Apple application) (iTranslate, 2020), help tourists to communicate with local residents and also enables the tourist to understand what is written in menus by reading and translating the menus in restaurants or hotels.

5. Optimization Services

Service providers can optimize their services using artificial intelligence with the Maximum Likelihood Estimation algorithm (Samala et al., 2020). Since optimization services are based on optimizing a service provided, it often occurs in the tourism and hospitality industry in the form of fare and rate forecasting, and tourism demand forecasting. Businesses adopt a dynamic pricing system by using this algorithm to make price estimations and adjust their prices in periods of low or high demands.

5.1. Fare and Rate Forecasting

One of the areas where artificial intelligence applications emerge in the tourism and hospitality industry as optimization services is fare and rate forecasting. Room occupancy rates can now be estimated with various machine learning models and artificial intelligence applications. For example, the ARIMA model (Chow et al., 1998), neural network approach (Law, 1998), big data (Pan & Yang, 2017), and Bayesian compression methods (Assaf & Tsionas, 2019) are among the methods used to estimate room occupancy rates. In addition, accommodation businesses can benefit from artificial intelligence applications regarding the prices of their rooms. Besides, as tourists are very price-sensitive, they want to know when the best time is to purchase or when the best, most affordable price will be. Some web pages help tourists in this regard. For example, some web pages help tourists to predict when to get the best offer and when to make the best purchase by directing some questions, such as "When is the best time to buy airline tickets?" (Schwahn, 2017) or "Here's exactly when to buy plane tickets to get the best deals" (Martin, 2018). Hopper and KAYAK websites are corporate websites that provide support to tourists in predicting unpredictable prices in the tourism and hospitality industry (Huang et al., 2019).

5.2. Tourism Demand Forecasting

Multi-layer perceptron networks, which are among the models of artificial neural networks (Claveria et al., 2015; Kon & Turner, 2005; Law, 2000; Law & Au, 1999), and deep learning methods (Law et al., 2019) are widely used in forecasting tourism demand. Moreover, support vector machine (Chen & Wang, 2007; Chen et al., 2015; Hong et al., 2011), a composite search index (Li et al., 2017), the fuzzy time series (Tsaur & Kuo, 2011; Wang, 2004), Gaussian processes (Tsang & Benoit, 2020) are used in forecasting tourism demand.

Such methods allow one to estimate the demand for the region, destination, or businesses periodically, and businesses update their prices through dynamic pricing according to these estimations.

In this regard, destinations may intensify advertisement and promotion activities during periods when demand is expected to be low to increase the demand.

5.3. Search Engine

Search engines are becoming increasingly essential for travel planning in the tourism and travel industry and attract destination marketing organizations' attention as an essential element in their marketing activities (Fesenmaier et al., 2011, p. 587). Those who will be traveling use search engines to make a travel plan consisting of accommodation, attractions, tours, restaurants, and activities in the region and decide on the regions they will travel to by the search engines' recommendations. As optimization services, they are used by tourists for hotel reservations or flight ticket purchases (Samala et al., 2020). For example, the search engines "Utrip" and "Avvio" use machine learning algorithms to assist their partner airlines, convention and visitor bureaus, hotels, and destination marketing organizations in providing customized travel advice for their customers. Utrip provides travel suggestions to the customers upon request within seconds, according to a number of variables, such as their interests, preferences, locations, and budgets, and customers can make purchasing by such travel suggestions (Abadicio, 2019).

5.4. Consultancy Services

Artificial intelligence applications can also be used by businesses providing consultancy services in the tourism and travel industry. These businesses offer recommendations similar to the search engine; the difference is that these businesses work in close cooperation with travel or accommodation businesses. For example, AltexSoft, a Ukrainian-based B2BN company, cooperates closely with travel and hospitality businesses to develop unique software and systems thanks to their data and machine learning teams and provides consultancy to these tourism businesses with regard to booking and reservation, travel management, and airline management by using natural language processing, automation, and machine learning models (Abadicio, 2019).

6. Other Artificial Intelligence Applications in the Tourism and Hospitality Industry

In terms of other artificial intelligence applications in the tourism and hospitality industry, this section presents the most common examples of technologies that tourists can use on their own, which can be called self-service technology.

6.1. Self-Service Check-In and Check-Out Kiosks

Self-check-in and check-out information kiosk is a technology that has just begun to be adopted in the hospitality industry, allowing guests to perform their check-ins and check-outs on their own without visiting the reception (Kim & Qu, 2014, p. 227). Yotel New York offers its guests to do their check-ins quickly and easily with self-service kiosks, like those at airports, without waiting at the reception (Yotel New York, 2020). Such kiosks are also used at airports. Self-service kiosks at airports allow passengers to check-in, print their boarding passes (Future Travel Experience, 2013), and check-in luggage (Nicas & Michaels, 2012) without any staff assistance.

6.2. Artificially Intelligent Virtual Assistant

Wynn Las Vegas announced in 2016 that it planned to equip all of its rooms with the Echo system, a hands-free voice-controlled speaker from Amazon. This application is a first in the world, allowing guests to control many technologies in the room with voice commands to the virtual assistant Alexa, the brain behind Echo technology (Hotelmanagement.net, 2016). Also, virtual assistants can connect to travel agencies' web pages and assist the guests about the activities in the destination, flight and accommodation reservations (Ivanov et al., 2017, pp. 1511-1512). Divan Istanbul offers the smart virtual assistant "Assista" to the service of its guests in cooperation with Arçelik, allowing guests to use their voice commands to turn on or off lights and curtains, change air conditioning settings, and access information about the weather, exchange rates, news summaries, traffic and road conditions, and the best restaurants and events in the city (CHIP Online, 2018). In addition, a virtual assistant named SARA, which has an automatic tourist information system in Singapore and provides information about the city, is at the service of tourists. Tourists can communicate with SARA by speech, typing, or QR code scanning, and they can visit the city without any human assistance according to the information provided by SARA (Niculescu et al., 2014).

D. Artificial Intelligence, Robotic Technologies, and Their Possible Impacts on the Future of the Tourism and Hospitality Industry

Considering the historical development of artificial intelligence and robotic technologies, it is a known fact that these technologies will be the ones that people will frequently use in their daily and professional lives in the next few decades. In this context, it is predicted that the use of artificial intelligence and robotic technologies will become more widespread in the tourism and hospitality industry. Current practices point out that these technologies are used in the front office and food and beverage departments, which frequently interact with the guests. However, their usage is limited in the housekeeping department. In the following years, it is foreseen that these technologies will be used in laundry and housekeeping services, such as room cleaning, folding sheets and towels, and moving and collecting dirty sheets to a particular area (Yang et al., 2020). With the transformation of the rooms into smart ones, it is likely that the guests will control the lights, curtains, air conditioning, TV, room temperature, and smart room systems through virtual assistants that are installed in the rooms and sensitive to the voices of the guests. The future also expects technologies such as detecting the guest's mood in the morning with artificially intelligent visual and audio systems and creating scenes on the walls by its mood to make the guest feel of being awakened. Ordering via mobile applications powered by artificial intelligence is another technology that is likely to become widespread in hotels. Keeping a record of the guest's past experiences on this technology will enable the guest to view the past orders once launching the application and place orders quickly by saving time, which can be considered a situation that increases guest satisfaction and quality of experience. Furthermore, the use of artificial intelligence and robotic technologies, which emerge in the form of robot receptionists, robot bellboy, robot concierge, and self-service check-in and check-out kiosks in the front office department, will become more widespread in the coming years.

These technologies have started to be used very often in the food and beverage departments in hotels and restaurants, especially in technology-intensive countries. In such food and beverage businesses, the guest's order can be taken on the order screen next to the table, via the QR (Quick Response) code, or by the robot waiter, be prepared by robot chefs in the back of the house with the beverages mixed by a robot bartender, and be delivered to the guests with conveyor belts, robot waiters, or robot bussers (Yang et al., 2020). The quality of the service can be a factor that increases the experience and satisfaction of a tech-savvy guest. Perhaps the most common artificial intelligence technologies to be used in this area are drones. Nowadays, drones are frequently used in many sectors for image and video purposes, and they appear in food delivery service in the food and beverage industry. Current practices with drones imply that food delivery service with drones will become widespread in the coming years, which is still in trial stages and being piloted.

Artificial intelligence technologies are used in meeting and event management on the basis that the participants attending the meeting should enjoy and have fun at a meeting. Ensuring a participant to attend meetings with a pre-assigned QR code badge and the artificial intelligence program's recognizing the participant from the QR code and greeting it by SMS or showing its name on the screen will increase the satisfaction of the participant. In addition, it is anticipated that enabling a large number of participants from different locations of the world to participate in a meeting with mobile telepresence robots will take its place in the industry as an increasingly widespread practice in the coming years because participants will have saved time and accommodation and transportation costs.

Golf is known as an expensive sports branch, among others. There are many accommodation businesses that specialize and invest in golf tourism, especially in the Belek/Antalya, Turkey. These businesses employ staff specialized in this field to meet the guests' needs and requests in the golf courses. The staff maintains courses, uses buggies to help guests reach golf courses and different points within these courses, and collects golf balls. At the same time, there are personnel in charge of mowing the growing grass. In the next few decades, it seems likely that the mowing will be assigned to robots; the buggies will be driverless and move with navigation by the guest's instructions; and drones will do the ball collecting work.

In the context of the travel and transportation industry, facial recognition systems, which are still in the pilot implementation stage at airports, are technologies based on passengers' biometric data. Passengers will be able to pass passport control quickly and save time thanks to these technologies. It is anticipated that the pilot implementations of such technologies will be completed in the coming years, and they will become widespread in airports, which are considered hubs in almost every country. In addition to airports, travel agencies appear among other types of businesses in the travel and transportation industry, where artificial intelligence and robotic technologies are used. Travel agencies will be using artificial intelligence applications frequently not only for forecasting tourism demand but also as chatbots and robot guides in the coming years. Robot guides will be able to play an active role in introducing historical and archaeological sites to guests in their own language. It is thought that robots will be deployed for room cleaning or deck cleaning in cruise tourism, and it will be one of the main goals to increase the satisfaction and experience of guests by developing the capabilities of robot bartenders and robot chefs.

It is also possible to use IoT (internet of things)-based information systems for hot air ballooning, which is considered a very important attraction in tourism. In this context, as a result of the automation and evaluation of the existing data collected, it is expected to save work and time, and to implement systems that allow safe flights with more accurate measurements (Özen, 2020).

The use of robot guides in museums is still in its infancy. Robot guides serve to increase visitors' existing knowledge by showing them around and providing relevant information about the features of the artifacts exhibited in the museum. It can be anticipated that the use of these guide robots in museums will increase in the future. In addition, virtual guides, which are among other the artificial intelligence technologies used in museums, have started to be deployed in many museums but will be available to visitors in almost all museums in the future.

It is a known fact that the use of artificial intelligence and robotic technologies will increase in the tourism industry, as indicated in the relevant studies. Therefore, it is deemed necessary to emphasize some impacts of these technologies on the tourism sector. These technologies primarily have impacts on employees. These technologies are generally perceived as the ones that can replace the staff; however, they should be considered technologies that will help the staff and increase the service quality. They will be able to contribute to the more comfortable and more efficient execution of daily operations. In addition, artificial intelligence and robotic technologies will bring out new types of professions and be perceived as technologies that can extinguish some existing professions. However, they can be used effectively in tourism with such new professions they will bring out. Another impact on employment is that they are technologies that can be a solution to labor turnover (Ivanov & Webster, 2017; Kuo et al., 2017; Shamim et al., 2017). Nowadays, employees can change their places very often for various reasons, and businesses may have difficulties replacing them. The increasing use of robotic technologies in these businesses will prevent this adverse situation and create a workforce that can work 24/7. Besides, deploying robotic technologies in night shifts, where many people are unwilling to work, blink as a solution, especially for accommodation businesses. In addition to all these, the deployment of robots will prevent thefts at sales points and revenue loss.

Artificial intelligence and robotic technologies also have an impact on guests. As can be implied from the studies on the use of these technologies in the tourism and hospitality industry and their impacts on guests, guests' experience and satisfaction will increase, leading technology-oriented guests to pay more voluntarily. In addition, humanoid appearance and their interaction and verbal communication capabilities, which are indispensable for the service sector, can be considered another issue that satisfies the guests. The speed, punctuality, and delivery style of services offered by robots will positively affect the service quality perceived by guests.

These technologies have a number of impacts on the operations and financial budgets of businesses as well as staff and guests. First of all, these technologies can increase the production capacities and sales of tourism and hospitality businesses and reduce production, staff, and stocking costs, which inevitably have significant positive effects on businesses in financial terms. Therefore, it is expected that businesses seeking such advantages will make their ecosystems, operations, and available physical buildings suitable for the use of robots. Besides, staff should be offered training about the usefulness and assistive nature of these technologies and how to utilize them. Including courses on the benefits and use of artificial intelligence and robotic technologies and how to optimize human-robot interaction in higher education curricula will enable students, who are potential sector employees, to perceive these technologies as auxiliary staff, not a threat.

It is supposed to be important that tourism and hospitality businesses and destinations desiring to gain a competitive advantage in the international tourism market utilize such technologies. The high initial setup costs may prevent many businesses and destinations from investing in these technologies. However, the reputation and brand image of businesses and destinations will be fostered with these technologies, and the competitive advantage will make them more preferred ones. At the same time, the use of such technologies in marketing activities will similarly increase the power of those businesses or destinations in the market. On the other hand, the host countries of such businesses and destinations must have appropriate infrastructures to invest in these technologies or develop their existing infrastructures to use them. It is important to eliminate the obstacles in the current laws or prepare a legal basis that facilitates the use of these technologies in businesses and destinations. Moreover, it seems likely that countries will gain extra tax revenues with the use of robots in the tourism and hospitality industry (Ivanov & Webster, 2020).

The use of artificial intelligence and robotic technologies in the tourism and hospitality industry has potential risks and ethical concerns as well as desirable impacts. For example, it becomes difficult to use such technologies in tourism and hospitality businesses seeing that all guests from different nationalities may experience difficulties adopting or accepting these technologies due to cultural differences, age, and traditional orientation. In addition, staff not accepting these technologies, because they think these technologies will replace them, is one of the challenges businesses will face in the coming years. Another point is that if these technologies communicate with other devices through sensors within the scope of the "internet of things," it is likely that artificial intelligence programs will get out of control. Finally, the biggest challenge of these technologies is the cybersecurity problem. Since these technologies operate connected to the internet, they are prone to cyberattacks; therefore, all kinds of personal data obtained from guests through such technologies should be kept strictly confidential with relevant measures.

Conclusion and Recommendations

Although the adoption of artificial intelligence applications and robotic technologies is not often welcomed by the tourism and hospitality industry, these technologies have gradually become a part of our lives with the effect of the developments in the technology age. At this point, the question is, "Will robots be able to offer the services at least as well as humans with the help of artificial intelligence?" This question should be responded to in light of the future developments with the artificial intelligence applications and robotic technologies being used today, discussed comprehensively within the scope of this study. As a matter of fact, it is known that the aforementioned artificial intelligence applications and robotic technologies are predominantly projected, developed, and implemented as a result of several scientific studies. Although the tourism and hospitality industry stakeholders still have difficulties in obtaining qualified human resources, they have difficulty accepting these technological developments. On the one hand, a large number of people focus on developing themselves both theoretically and practically for such a human-oriented sector; on the other hand, it is an indisputable fact that unmanned technologies are being developed at full speed to replace these people. Another question that needs to be addressed is, "Is the main purpose to provide a completely unmanned service or to increase the service quality by helping qualified staff?" Although it is quite challenging to answer this question, any service provided without a human touch always fail to satisfy consumers' demands and needs due to the nature of the tourism and hospitality industry. Concepts, such as feeling, emotion, smile, and sincerity, are indispensable for hosting, and artificial intelligence technologies and service robots cannot be expected to evoke such concepts, like a human. In other words, although there have been technological developments in the tourism and hospitality industry, it is not possible to talk about "service" and "hospitality" without people. Literally, it is most likely for artificial intelligence applications and robots to be recognized as important elements that help tourism staff, not replace them, and even serve in new professional positions.

Although the general view regarding the adoption of artificial intelligence applications and robotic technologies is now conservative and cautious, these technological developments have tangible benefits for administrative staff, businesses, operators, suppliers, employees, consumers, and many other stakeholders. In terms of tourism policies and planning, administrative staff can be empowered for better future projections and healthier decisions with the help of precise predictions of artificial intelligence applications. They can also provide benefits in managing the tax on tourism revenues. In terms of workforce and employment, service robots can be advantageous for businesses in the tourism and hospitality industry with high personnel turnover. On the other hand, consumers, who want to experience a different service concept, can have the experience of receiving services from robots, machines, or humanoid robots, willing to pay more to businesses. In terms of minimizing service errors, they may be likely to increase service quality and indirectly ensure customer satisfaction and loyalty. They can also play an influential role in increasing production and reducing operating costs in the long run. When evaluated for operators and business managers, artificial intelligence applications and robotic technologies can significantly benefit marketing management, increase competitiveness, and provide a competitive advantage against other businesses. Even though it is noted that the increasing demand for service robots, especially in accommodation and food and beverage businesses, is due to the desire of consumers to have the aforementioned experience, service robots may be developed further and perform tasks that can help people, even if not as much as a human. In this context, countries need to have an infrastructure suitable for these technologies or to develop their existing infrastructure and to make relevant legal regulations to utilize these applications and technologies.

It is also imperative to include these technologies in higher education curricula and to conduct further studies on how to optimize human-robot interaction. Students enrolled in relevant programs should be encouraged to know artificial intelligence applications and robotic technologies and carry out joint projects with academics in engineering departments. Hence, exchanging ideas with people who know the nature of the industry may lead different technologies to be developed to satisfy consumers' needs and demands. For example, these technologies appear as waiters, bussers, and hosts/hostesses in the service area, as well as chefs in the kitchen, automation devices, conveyors, or drones in hospitality management or in food and beverage management. Many technologies that have not been thought of until today can only be possible with academic circles and industry practitioners forming joint working groups and creating outputs. Similar developments may occur for travel agencies, airports, museums, and transportation companies, which are essential stakeholders of the tourism and hospitality industry.

Lastly, the issue related to technology acceptance of guests and employees should also be seen as such significant threats that guests' not being technology-oriented, not accepting new technologies, reluctance to use these technologies, and staff's not adopting these technologies should be considered as possible obstacles. Another critical challenge - perhaps the most important one - is that these internet-based technologies raise cybersecurity concerns, and consequently, ethical concerns, such as privacy and confidentiality. At this point, it is relatively important that the tourism and hospitality industry should overcome such obstacles in the use of artificial intelligence applications and robotics technologies. With the disappearance of question marks for both internal and external stakeholders of the industry, it is inevitable that they follow and use these technological developments in the future.

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ARTICLES FOR FACULTY MEMBERS

AUTOMATED SOLAR AND ELECTRIC COMPOST BINS FOR THE TOURISM AND FOOD & BEVERAGE (HOTEL) INDUSTRIES

Assessing agri-food waste valorization challenges and solutions considering smart technologies: An integrated fermatean fuzzy multi-criteria decision-making approach / Zhang, Q., & Zhang, H.

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Article

Assessing Agri-Food Waste Valorization Challenges and Solutions Considering Smart Technologies: An Integrated Fermatean Fuzzy Multi-Criteria Decision-Making Approach

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Abstract: With the growth of the worldwide population and depletion of natural resources, the sustainable development of food systems cannot be ignored. The demand for agri-food waste valorization practices like high-value compounds production has received widespread attention; however, numerous challenges still exist. The present study aims to identify those challenges of agri-food waste valorization and propose effective solutions based on smart technologies. Based on a systematic review of the literature, the study combs existing challenges of agri-food waste valorization and constructs a six-dimension conceptual model of agri-food waste valorization challenges. Moreover, the study integrates a Fermatean fuzzy set (FFS) with multi-criteria decision-making (MCDM) methods including stepwise weight assessment ratio analysis (SWARA), decision-making trial and evaluation laboratory-interpretative structural modeling method (DEMATEL-ISM), and quality function deployment (QFD) to evaluate the weights of each dimension, find causal interrelationships among the challenges and fundamental ones, and rank the potential smart solutions. Finally, the results indicate that the "Government" dimension is the severest challenge and point out five primary challenges in agri-food waste valorization. The most potential smart solution is the "Facilitating connectivity and information sharing between supply chain members (S8)", which may help government and related practitioners manage agri-food waste efficiently and also facilitate circular economy.

Keywords: agri-food waste valorization; smart technology; Fermatean fuzzy set; SWRAR; DEMATEL-ISM; QFD

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1. Introduction

In the face of a mounting global food crisis, where millions of people grapple with severe food insecurity, the issue of agri-food waste stands as a stark contradiction, exacerbating the problem. The 2024 Global Report on Food Crises by the Food and Agriculture Organization (FAO) highlights that despite the dire need, approximately 281 million individuals worldwide suffer from inadequate access to nutritious food, while an astonishing 1.3 billion tons of food waste is generated annually, accounting for 13.8% of global food production [1,2]. Of particular concern is the agri-food system, which not only contributes significantly to this waste but also bears the brunt of its environmental consequences [3,4]. The prevalent practice of landfilling agri-food waste not only squanders valuable resources but also emits greenhouse gases and pollutes groundwater, posing a threat to both ecological balance and human health. Indeed, different from other waste, agri-food waste, rich in complex carbohydrates and bioactive compounds, presents a treasure trove of untapped potential for the production of value-added products [5]. To be specific, an abundance of biochemicals are plant-derived, with a lesser amount derived from animals including pomace, peels, leaves, meat by-products, and so on [6]. Those bioactive compounds constitute a broad spectrum of molecules with unique structures and properties. They can be utilized in the manufacture of bio-fertilizers, fuel, compost, cosmetics, and functional foods [7]. Thus, the valorization of agri-food waste (AFW) has emerged as a possible way for the transformation and sustainable development of the global agri-food system to be realized [8]. It is also considered to have a substantial impact on the United Nations' Sustainable Development Goals, particularly SDG 2 (zero hunger) and SDG 12 (responsible consumption and production) [9]. By transforming agri-food waste into value-added products like bio-fertilizers, fuel, compost, cosmetics, and functional foods, the valorization process reduces food waste and contributes to food security. This directly aligns with SDG 2, which aims to end hunger and achieve food security and improved nutrition. Moreover, valorizing agri-food waste promotes circular economy practices, reducing waste generation and encouraging the use of resources more efficiently. This not only mitigates the environmental impact of waste disposal but also fosters sustainable production and consumption patterns. Overall, successful agri-food waste resource utilization can bring significant economic, environmental, and social benefits (Table 1).

Table 1. Benefits of successful agri-food waste valorization.

Economic	Environmental	Social
Increasing revenue sources: High value-added products can create new sources of income.	Reducing greenhouse gas emissions: Resource utilization can reduce emissions from incineration.	Enhancing public awareness: Successful resource utilization cases can promote public participation in waste management.
Saving costs: By optimizing waste management processes, waste disposal cost can be reduced.	Conserving water: Extracting valuable compounds from waste can reduce dependence on natural resources, especially water resources.	Creating employment opportunities: Developing waste resource utilization industry requires human resource support, creating new employment opportunities.
Bringing investment return: The investment of the government and enterprises can bring long-term economic returns.	Protecting ecological environment: Resource utilization can reduce waste pollution to soil, water and air, and protect the diversity of ecosystems.	Increasing social trust: Transparent and traceable waste management processes can enhance consumer trust in product.

In fact, the full utilization of agri-food waste for production of value-added materials remains largely untapped, although its considerable potential has been recognized [10]. On one hand, the valorization of agri-food waste is challenged by its intrinsic complexity, which is marked by heterogeneous composition, short lifespan, distribution pattern [11], and environmental sensitivity. Taking heterogeneous composition for instance, agri-food waste comprises a wide variety of materials, including pomace, peels, leaves, meat by-products, etc. Each component has unique biochemical properties, requiring tailored processing methods. On the other hand, the operations of agri-food waste valorization encompasses a multifaceted procedure including gathering, transportation, storage, treatment, and final disposal [12]. During these processes, a range of challenges, including environmental, social, and economic issues, are likely to emerge [13,14]. Hence, it is imperative to sort out and analyze the barriers that hinder the execution of agri-food waste valorization.

The aforementioned dual barriers to valorizing agri-food waste have persisted as enduring challenges, proving recalcitrant to resolution via conventional technological means. Recent advancements have seen a notable rise in innovative waste management strategies that harness smart technologies aligned with Industry 4.0 principles for enhanced efficiency and effectiveness. For instance, smart technologies facilitate the transition from conventional waste management systems to novel frameworks incorporating smart sensors, enabling real-time monitoring and fostering a sophisticated management infrastructure. Pertaining to the agri-food sector, a myriad of smart technologies, particularly big data analytics (BDA), blockchain, artificial intelligence (AI), Internet of Things (IoT), digital twins, smart sensors and robotics, and Information and Communication Technology (ICT), could revolutionize traditional practices, enhance efficiency, and promote sustainability [15]. The integration of AI, BDA, and IoT technologies can facilitate the application of automation and robotics in waste management, which reduces labor costs and human errors. Through IoT technology, combined with blockchain, RFID tags, and GIS, the entire agri-food supply chain can be tracked, which helps to promptly identify and respond to potential risks, ensuring the safe disposal and reuse of waste. Artificial intelligence (AI), which involves programming computers to mimic human behaviors like machine learning, artificial neural networks, and deep learning, offers immense potential for data-driven science within agri-food supply chains, especially synergized with high-performance computing technologies [16]. Moreover, some business modes comprehensively leverage big data analytics (BDA) to extract value from agri-food waste, thereby optimizing the existing linear supply chain [17]. Likewise, through the integration of smart technology and e-commerce, a digital platform could address the inefficiencies in agri-food waste management by aggregating and analyzing waste data, and identifying potential business collaborators who may repurpose agri-food waste into commercially valuable products [18]. Nevertheless, the introduction of these technologies in organizations without meticulous planning and scientific analysis is doomed to be unproductive and may even incur substantial financial burdens for the organizations [12]. As a result, it is crucial to contemplate mitigation strategies combining smart technologies, particularly in the context of specific challenges associated with the valorization of agri-food waste.

This study aims to tackle several critical research questions:

Identify and prioritize challenges: Uncover the primary obstacles that hinder the socialization and standardization of agri-food waste valorization;

Assess challenges priority: Determine the challenges that should be addressed first, considering their priority and limited resources.

Systematize interrelationships: Systematically map the intricate causal and hierarchical relationships among these challenges.

Explore smart technological solutions: Identify and evaluate the most effective smart technological solutions considering all factors comprehensively.

Guided by these research questions, the objectives of this paper are as follows:

Objective 1: Identify and prioritize the challenges associated with agri-food waste valorization.

Objective 2: Clarify the underlying causal and hierarchical relationships among these challenges.

Objective 3: Determine the smart technological solutions and validate the most feasible options for addressing challenges in the valorization of agricultural food waste.

To achieve these objectives, this study scrutinizes existing challenges in agri-food waste valorization and formulates a six-dimension conceptual model. Then, the Fermatean fuzzy stepwise weight assessment ratio analysis (FF-SWRAR) is applied to evaluate the significance of each dimension and challenge. Following this, the Fermatean fuzzy decision-making trial and evaluation laboratory-interpretative structural modeling method (FF-DEMATEL-ISM) is employed to discern cause-and-effect dynamics among the identified challenges and core challenges. Finally, the Fermatean fuzzy quality function deployment (FF-QFD) aids in ranking prospective smart technological solutions.

To the best of authors' knowledge, prior study has not thoroughly investigated smart technological solutions for agri-food waste valorization. While a study has touched upon the integration of smart technology with biowaste valorization, it has been confined to a narrow perspective, such as the application of AI [19]. Additionally, our work firstly introduces an integrated framework that combines FFS, SWRAR, DEMATEL-ISM, and QFD methodologies, a combination that has never before been utilized to comprehensively assess both the challenges and potential solutions in agri-food waste valorization. Therefore, the study may provide valuable insights for related policymakers to devise strategies aimed at enhancing the valorization of agri-food waste, thereby contributing to the circular economy. Similarly, the agri-food waste valorization industry is expected to benefit from the study's findings, which will guide the formulation of more effective and sustainable decisions.

2. Literature Review

This section discusses the concepts as challenges of agri-food waste valorization, smart technologies in agri-food system, and MCDM methods in waste management. At the end of the section, the research gap is highlighted.

2.1. Challenges of Agri-Food Waste Valorization

Currently, the majority of studies concerning the challenges of agri-food waste valorization predominantly concentrate on the exploration of a particular type of agri-food waste or a distinct valorization methodology from the viewpoints of biology and chemistry. For instance, considering the valorization of agri-food waste derived from olive oil and wine production, Tapia-Quirós et al. have advocated for the recovery of phenolic compounds as an effective way and elucidated techniques available for the analysis, extraction, and refinement of polyphenols from the olive mill and winery by-products [20]. Also, Mannaa et al. have proposed the integration of insects with organic waste in the bioconversion processes and accentuated the prospective efficacy of these biorefinery systems in surmounting the prevailing challenges associated with agri-food waste [21].

There are few works in the literature that study the challenges of agri-food waste valorization from a holistic perspective. Berenguer et al. have discussed some pivotal challenges in the valorization of agri-food wastes based on several perspective applications [6], so the scope of challenges identified are limited and the study lacks quantitative research and fails to probe into the significance and intrinsic interrelations of these challenges.

2.2. Smart Technologies in the Agri-Food Sector

The technological prowess of corporations is crucial in driving their innovative endeavors, which is viewed as one of the most significant dynamic competencies required to maintain enduring competitiveness [22]. In agri-food sector, the application of smart technologies provides the sustainable solutions to different agricultural problems [23]. Therefore, multiple studies have investigated the application status and emerging trends of smart technologies in the agri-food sector [24–26]. In terms of different regions, developed countries tend to exhibit a greater engagement with smart technologies [27]. Furthermore, among various smart technologies, the application of blockchain in agri-food supply chain has received more attention [28,29]. Similarly, regarding stakeholders within the agri-food supply chain, downstream companies are more willing to embrace smart technologies to cope with the uncertainty of the supply chain [30].

It is worth noting that although there is research in the literature introducing smart technologies for waste prevention and reduction in the agricultural food industry [31], it remains essential to thoroughly analyze the specific challenges encountered during the valorization of agri-food waste to determine the smart technological solutions that can be effectively employed and their priority in addressing these challenges.

2.3. MCDM Methods in Waste Management

Multi-criteria decision-making (MCDM) is a valuable approach for tackling complex decision-making scenarios where multiple criteria need to be taken into account [32]. It provides a structured framework to ensure a more informed and rational choice. In this context, it is evident that MCDM techniques are advantageous, as they enable a systematic comparison of challenges and strategies. Furthermore, it is common for decision-makers to articulate their subjective judgments through linguistic expressions in reality. This practice poses challenges when attempting to precisely model such information using crisp values. Consequently, to accommodate this imprecision, fuzzy set theory has been widely utilized in various cases [33].

In previous research related to waste management, fuzzy MCDM techniques have been commonly employed to assess challenges and formulate effective strategies. For example, Çelik et al. apply intuitionistic fuzzy multi-criteria decision-making (IFMCDM) methods to identify the most effective hospital for medical waste management in Erzurum, Turkey [34].

Komal integrates intuitionistic fuzzy sets (IFSs) with the weighted aggregated sum product assessment (WASPAS) method to assess health-care waste disposal methods [35]. Kabirifar et al. design a hybrid fuzzy MCDM approach to analyze nineteen factors influencing the management of construction and demolition waste [36].

The research methodology of this paper is developed based on a study conducted by Karuppiah [37]. The researcher combines Fermatean fuzzy set (FFS) with AHP, DEMATEL, and TOPSIS to explore e-waste mitigation strategies. In order to enhance the operability and pertinence of problem analysis, this study introduces another integrated Fermatean fuzzy multi-criteria decision-making approach (i.e., FF-SWRAR, DEMATEL-ISM, and QFD). In contrast to AHP, SWARA necessitates fewer pairwise comparisons for ascertaining weights, thereby rendering it a user-friendly approach for decision-makers [38]. Additionally, QFD is more oriented towards tackling specific issues, while TOPSIS primarily concentrates on the relative gaps between solutions [39].

2.4. Research Gap

Based on the above review and analysis, it is evident that while certain studies have explored agri-food waste management from specific perspectives, there remains a dearth of comprehensive examinations regarding the global challenges associated with agri-food waste valorization. Furthermore, the majority of existing research introduces the application of smart technology in the agri-food sector, yet lacks a quantitative analysis. This study endeavors to bridge the gaps by introducing a holistic evaluation framework for agri-food waste valorization challenges and solutions within uncertain environments that not only conduct an exhaustive investigation of diverse factors but also probe into their intricate relationships.

3. Methods

This section is comprised of the two following subsections: preliminaries and the research framework. In first subsection, the definition of FFS and related operation rules will be introduced in detail. In the second subsection, the overall research framework, including three major stages and integrated four-part methodology (i.e., FFS-SWRAR-DEMATEL-QFD), is described thoroughly, as shown in Figure 1.

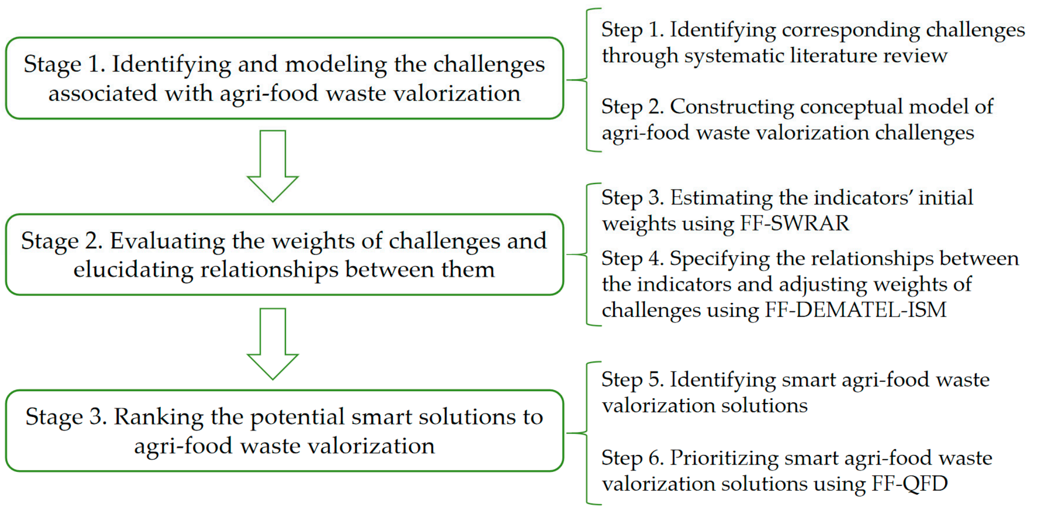

Figure 1. Research framework.

3.1. Preliminaries

3.1.1. Definition of Fermatean Fuzzy Set

Definition 1. *Assuming that X is a universe of discourse, a Fermatean fuzzy set F on X is defined by Senapati and Yager as a function that applied to χ [40]:*

$$F = \{\langle \chi, \mu_F(\chi), \nu_F(\chi) \rangle | \chi \in X\} \tag{1}$$

where $\mu_F(\chi) \in [0,1], \nu_F(\chi) \in [0,1]$ denote the degree of membership and non-membership of element $\chi \in [0,1]$, respectively, satisfying $0 \le \mu_F(\chi)^3 + \nu_F(\chi)^3 \le 1$. For any FFS, the degree of indeterminacy of $\chi \in X$ to F is defined as:

$$\pi_F(\chi) = \sqrt[3]{1 - \mu_F(\chi)^3 - \nu_F(\chi)^3} \tag{2}$$

In addition, $F = (\mu_F, \nu_F)$ is called a Fermatean fuzzy number (FFN).

It is worth noting that FFS, an extension to IFS and PFS, has enlarged the domain of membership and non-membership, which is shown in Figure 2. Therefore, compared to IFS and PFS, FFS is more efficient in solving multi-criteria decision-making problems under uncertainty.

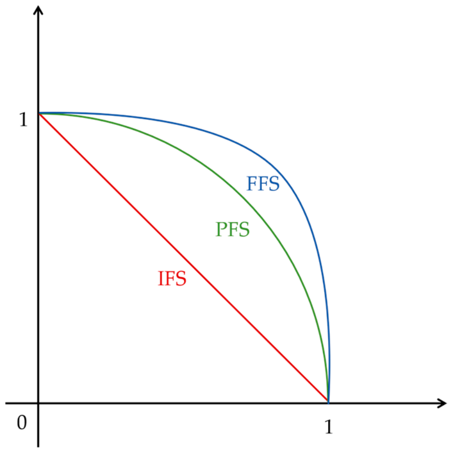

Figure 2. The comparison of IFS, PFS, and FFS.

3.1.2. Related Operations for Fermatean Fuzzy Set

Definition 2. *Let $F_1 = (\mu_{F1}, \nu_{F1})$ and $F_2 = (\mu_{F2}, \nu_{F2})$ be two FFNs, $\lambda > 0$, defined as [40]:*

1. $F_1 \oplus F_2 = (\sqrt[3]{\mu_{F1}^3 + \mu_{F2}^3 - \mu_{F1}^3\mu_{F2}^3}, \nu_{F1}\nu_{F2})$;
2. $F_1 \otimes F_2 = (\mu_{F1}\mu_{F2}, \sqrt[3]{\nu_{F1}^3 + \nu_{F2}^3 - \nu_{F1}^3\nu_{F2}^3})$;
3. $\lambda F_1 = (\sqrt[3]{1 - (1 - \mu_{F1}^3)^\lambda}, \nu_{F1}^\lambda)$;
4. $F_1^\lambda = (\mu_{F1}^\lambda, \sqrt[3]{1 - (1 - \nu_{F1}^3)^\lambda})$;

Definition 3. *Let $F = (\mu_F, \nu_F)$ be a FFN, the score function is defined as [33]:*

$$score(F) = \mu_F^3 - \nu_F^3 \tag{3}$$

For any FFN, $score(F) \in [-1, 1]$.

The accuracy function is defined as [33]:

$$accuracy(F) = \mu_F^3 + \nu_F^3 \tag{4}$$

For any FFN, $accuracy(F) \in [0,1]$.

According to score and accuracy values, the comparison between any two FFNs $F_1 = (\mu_{F1}, \nu_{F1})$ and $F_2 = (\mu_{F2}, \nu_{F2})$ is determined:

If $score(F_1) < score(F_2)$, then $F_1 < F_2$;
If $score(F_1) > score(F_2)$, then $F_1 > F_2$;
If $score(F_1) = score(F_2)$, then
If $accuracy(F_1) < accuracy(F_2)$, then $F_1 < F_2$;
If $accuracy(F_1) > accuracy(F_2)$, then $F_1 > F_2$;
If $accuracy(F_1) = accuracy(F_2)$, then $F_1 = F_2$.

Definition 4. *Let* $F_i = (\mu_{Fi}, \nu_{Fi})$ $(i = 1, 2, \ldots, n)$ *be a set of FFNs, then a Fermatean fuzzy weighted average (FFWA) is calculated [37]:*

$$FFWA(F_1, F_2, \ldots, F_n) = \left(\sum_{i=1}^{n} \omega_i \mu_{Fi}, \sum_{i=1}^{n} \omega_i \nu_{Fi}\right) \tag{5}$$

where $\omega_i \in [0,1]$ *is the weight of* F_i *with* $\sum_{i=1}^{n} \omega_i = 1$.

3.2. Research Framework

Stage 1. Identifying and modeling the challenges associated with agri-food waste valorization.

Step 1. Identifying corresponding challenges through a systematic review of the literature.

The following framework is adopted to collect articles relevant to agri-food waste valorization [41].

1. Identification: Searching articles considering five aspects in the following order: (1) source type, (2) source quality and relevance, (3) search engine, (4) search period, and (5) search keyword.

2. Screening: Excluding articles returned from the search that do not completely satisfy search criteria and some duplicate copies.

3. Eligibility: Assessing full text to make sure content relevance.

4. Inclusion: Performing a countercheck and a content analysis on the curated articles.

Step 2. Constructing conceptual model of agri-food waste valorization challenges.

5. Classifying and Modeling: Subsequent to the initial step of investigating and analyzing publications, the challenges of agri-food waste valorization are divided into a six-dimensional conceptual model by experts.

Stage 2. Evaluating the weights of challenges and elucidating relationships between them.

This stage predominantly uses FF-SWRAR to calculate initial weights of indicators. Then, the FF-DEMATEL-ISM method is applied to figure out causal relationship and influence degree among the identified indicators.

Step 3. Estimating the indicators' initial weights using FF-SWRAR.

6. Evaluating the expertise level of decision makers [42]: The expertise of each DM is appraised through linguistic expressions delineated in Table 2 along with corresponding FFS equivalents.

Table 2. Linguistic terms of decision makers' expertise level.

Linguistic Terms	Absolute Expertise (AE)	High Expertise (HE)	Moderate Expertise (ME)	Less Expertise (LE)	No Expertise (NE)
μ	0.95	0.75	0.55	0.3	0.1
ν	0.1	0.3	0.55	0.75	0.95

Let M represent the count of DMs within the collective. The expertise level of a given DM m, symbolized as $E_m = (\mu_{\mathrm{m}}, \nu_m)$, dictates the influence of the DM's assessment in the decision procedure. The crisp number reflecting a DM's assessment influence among all can be computed:

$$\eta_m = \frac{1 + \mu_m^3 - \nu_m^3}{\sum\limits_{m=1}^{M} (1 + \mu_m^3 - \nu_m^3)} \tag{6}$$

7. Constructing a linguistic decision matrix for the evaluation of indicators: The linguistic terms infer the linguistic assessment rating of an indicator and further turn into FFN (Table 3) [43]. Consider a FF evaluation matrix $Q = [q_{im}]$ provided by experts, where each element $q_{im} = (\mu_{im}, \nu_{im})$ denotes the corresponding FFN for the linguistic evaluation of DM m for indicator i.

Table 3. Linguistic terms of indicators.

Linguistic Terms	μ	ν
Absolutely Important (AI)/Absolutely High Related (AHR)	0.99	0.10
Very Strong Important (VSI)/Very High Related (VHR)	0.90	0.20
Strong Important (SI)/High Related (HR)	0.80	0.30
Important (I)/Medium High Related (MHR)	0.65	0.40
Equally Important (EI)/Exactly Equal Related (EER)	0.50	0.50
Unimportant (U)/Medium Low Related (MLR)	0.35	0.70
Strong Unimportant (SU)/Low Related (LR)	0.20	0.80
Very Strong Unimportant (VSU)/Very Low Related (VLR)	0.10	0.90
Absolutely Unimportant (AU)/Absolutely Low Related (ALR)	0.01	0.99

8. Combining decision makers' judgments: Let N represent the cardinality of indicator set where $n = 1, 2, \ldots, N$. Considering expertise weights, the judgments of all DMs on an indicator are aggregated as follows:

$$I_i = \left(\sum_{m=1}^{M} \eta_m \mu_{im}, \sum_{m=1}^{M} \eta_m \nu_{im} \right) \tag{7}$$

9. Calculating the comparative significance of each indicator: Firstly, the positive score of each indicator, symbolized as PS_i, is determined as: $PS_i = 1 + score(I_i)$.

Then, rank the indicators in descending order according to the values of PS_i.

Based on the order, the comparative significance CS_i of each indicator is calculated as:

$$CS_i = \begin{cases} 0 & i = 1 \\ PS_i - PS_{i-1} & i > 1 \end{cases} \tag{8}$$

10. Computing the indicator weights [44]: Firstly, the comparative coefficient CC_i is estimated as:

$$CC_i = \begin{cases} 1 & i = 1 \\ CS_i + 1 & i > 1 \end{cases} \tag{9}$$

Then, the recalculated weight q_i of each indicator is determined as:

$$q_i = \begin{cases} 1 & i = 1 \\ \frac{q_{i-1}}{CC_i} & i > 1 \end{cases} \tag{10}$$

Finally, the initial weight of each indicator is calculated as:

$$w_i = \frac{q_i}{\sum\limits_{i=1}^{N} q_i} \ i > 1 \tag{11}$$

Step 4. Specifying the relationships between the indicators and adjusting weights of challenges using FF-DEMATEL-ISM.

11. Establishing the FF direct relationship matrix: DMs make pairwise comparisons of indicators to obtain mutual influence strength using Table 4 [45], where influence data among the indicators are expressed by FFN.

Table 4. Linguistic terms of influence score.

Linguistic Terms	Influence Score	FFN
Very High (VH)	4	(0.9,0.1)
High (H)	3	(0.7,0.2)
Low (L)	2	(0.4,0.5)
Very Low (VL)	1	(0.1,0.75)
No influence (NO)	0	(0,1)

12. Constructing aggregate FF direct relationship matrix: Use FFWA operator to aggregate the judgments of multiple DMs as follows:

$$A = \begin{bmatrix} (\mu_{F11}, \nu_{F11}) \ (\mu_{F12}, \nu_{F12}) \ldots (\mu_{F1n}, \nu_{F1n}) \\ (\mu_{F21}, \nu_{F21}) \ (\mu_{F22}, \nu_{F22}) \ldots (\mu_{F2n}, \nu_{F2n}) \\ \ldots \\ (\mu_{Fn1}, \nu_{Fn1}) \ (\mu_{Fn2}, \nu_{Fn2}) \ldots (\mu_{Fnn}, \nu_{Fnn}) \end{bmatrix} \tag{12}$$

13. Defuzzification [46]: The FF defuzzification function φ is employed to turn the FFN matrix A into crisp number matrix X as follows:

$$\varphi_{ij} = 1 + score(\mu_{Fij}, \nu_{Fij}) \tag{13}$$

$$X = \begin{bmatrix} \varphi_{11} \ \varphi_{12} \cdots \varphi_{1n} \\ \varphi_{21} \ \varphi_{22} \cdots \varphi_{2n} \\ \cdots \\ \varphi_{\mathrm{n}1} \ \varphi_{n2} \cdots \varphi_{nn} \end{bmatrix} \tag{14}$$

14. Normalization: The new aggregate direct relationship matrix X is normalized using following equations:

$$G = s^{-1}X \tag{15}$$

where $s = \max(\max\limits_{1 \le i \le n} \sum\limits_{j=1}^{n} x_{ij}, \max\limits_{1 \le j \le n} \sum\limits_{i=1}^{n} x_{ij})$.

15. Constructing total relationship matrix T:

$$G = s^{-1}X \tag{16}$$

where I is the identity matrix.

16. Classifying indicators into cause and effect groups as follows:

$$D = \left(\sum_{j=1}^{n} t_{ij}\right)_{1\times n} = (t_i)_{1\times n} \tag{17}$$

$$C = \left(\sum_{i=1}^{n} t_{ij}\right)_{n\times 1} = (t_i)_{n\times 1} \tag{18}$$

The value of $C + D$ represents centrality, while the value of $C - D$ represents causality.

17. Adjusting the weights of challenges: Combine centrality and initial weights calculated by SWRAR to obtain final weights of challenge using weighted average method. The specific weights are determined by relevant experts.

18. Obtaining initial reachability matrix (IRM): According to the following formula, total relationship matrix T is converted to the initial reachability matrix R. The threshold λ can be set based on the sum of mean and standard deviation in statistical distribution, effectively reducing subjective influence [47].

$$R = \begin{cases} 1 & t_{ij} \geq \lambda \\ 0 & t_{ij} \leq \lambda \end{cases} \tag{19}$$

19. Constructing final reachability matrix (FRM): To obtain the FRM, the transitivity of the IRM is examined. According to the transitivity rule, if factor i has an impact on factor j, and if factor j affects factor k, then factor i also impacts factor k [48].

20. Partitioning level: A level partitioning operation was performed to acquire the reachability, antecedent, and intersection set.

Stage 3. Ranking the potential smart solutions to agri-food waste valorization.

In the stage, some solutions considering smart technologies are proposed to promote valorization of agri-food waste. Then, the FF-QFD method is utilized to prioritize them.

Step 5. Identifying smart agri-food waste valorization solutions.

21. Identifying strategies in the perspective of smart technologies: Based on the relevant literature and experts' suggestions in the field, some potential strategies are provided.

Step 6. Prioritizing smart agri-food waste valorization solutions using FF-QFD.

The steps of FF-QFD are explained as follows:

22. Specifying the indicators: The indicators (i.e., challenges and solutions) have been decided in step 1 and 4.

23. Obtaining the importance weights of challenges: Each challenge has been evaluated based on FF-SWRAR.

24. Defining relationships between challenges and solutions: DMs use the scale as in Table 2 to define the relationship matrix $R_{ij}(i = 1, 2, \ldots, n, j = 1, 2, \ldots, k)$. If there is no relationship between the challenge and solution, the cell is left blank.

25. Calculating the relative importance of solutions: The relative importance $RI_j(j = 1, 2, \ldots, k)$ of solution j is determined using FFWA operator as:

$$RI_j = \sum_{i=1}^{n} w_i R_{ij} = \left(\sum_{i=1}^{n} w_i \mu_{Fi}, \sum_{i=1}^{n} w_i \nu_{Fi}\right)(j = 1, 2, \ldots, k) \tag{20}$$

26. Creating correlation matrix: The correlations $S_{jj'}(j \neq j')$ between solutions are created using the scale as in Table 2. There are three states that described an interrelationship: positive (+), negative (−), or non-existent (designated by a blank box).

27. Calculating score value for positive and negative correlations: Aggregate DMs' judgments of correlation matrix by FFWA operator and calculate final score value.

28. Finding absolute importance for each solution [49]: The absolute importance $AI_j(j = 1, 2, \ldots, k)$ for solution j can be computed as:

$$AI_j = RI_j \oplus \sum_{j'=1}^{k} S_{jj'} \otimes RI_{j'}(j = 1, 2, \ldots, k; j' \neq j) \tag{21}$$

29. Obtaining final score value of solutions and ranking them: Use FF defuzzification function to obtain crisp value of each solution and prioritize these solutions.

The integrated Fermatean fuzzy MCDM approach, comprising FFS-SWRAR, FFS-DEMATEL-ISM, and FFS-QFD, significantly contributes to the comprehensive and structured analysis of agri-food waste valorization challenges and solutions. By addressing uncertainty through FFS, simplifying weight calculation with SWRAR, unraveling causal dynamics with DEMATEL-ISM, and prioritizing solutions with QFD, this approach ensures a more informed and rational decision-making process for policymakers and practitioners.

4. Results and Discussion

In the preceding section, the general outline of a complete study has been established. Detailed calculations and corresponding results of the FF-MCDM studies are described in the following subsections.

4.1. Results

According to the three main stages of research framework, the applied procedure based on FF-SWRAR, FF-DEMATEL-ISM, and FF-QFD is summarized as follows:

Stage 1. Identifying and modeling the challenges associated with agri-food waste valorization.

Step 1. Identifying corresponding challenges through a systematic review of the literature.

The Web of Science databases were utilized to search for the following topics: "agri-food waste management", "agro-food waste management", "agri-food waste valorization", and "agro-food waste valorization". This search yielded 573 publications spanning from 2019 to April 2024. Following a series of screening procedures, a refined compilation of 43 articles was selected for further analysis. Then, the challenges of agri-food waste valorization were identified.

Step 2. Constructing conceptual model of agri-food waste valorization challenges.

Based on the literature [50], experts categorized the challenges into six distinct dimensions: organization, environment, technology, economy, government, and society. In this study, the classification framework could be constructed from a systems theory perspective. In this framework, the government, organization, and consumer are stakeholders of the agri-food waste valorization system, which constitute the internal core components, while the environment, economy, and technology are supporting and influencing factors, which constitute the external conditions for the operation of the system (Table 5).

Table 5. Conceptual model of agri-food waste valorization challenges.

Dimensions	Codes	Factors	Codes	References
Organization	C1	Poor logistical and infrastructural systems	C11	[51–54]
		Less standardized operational practices	C12	
		The absence of intermediary companies/departments collecting and directing wastes to specific points for processing	C13	
		Rare cooperation between supply chain members in the process of agri-food waste valorization	C14	
		Lack of instructions about approaches of agricultural waste valorization	C15	
		No safety assessment of biotechnologically materials	C16	

Table 5. *Cont.*

Dimensions	Codes	Factors	Codes	References
Environment (including biochemical property)	C2	The region-dependent and seasonal availability of a waste stream	C21	[55–58]
		Variable quality of the waste stream due to deterioration	C22	
		New product safety issues like contamination of heavy metals	C23	
		High sensitivity of microorganisms to operating conditions	C24	
		High standard on properties of the raw materials like element proportion, moisture content	C25	
		Production of environmental footprint in extraction processes	C26	
Technology	C3	Lack of the most efficient and cost-effective extraction method for specific waste streams	C31	[54,59–62]
		Limited technological capabilities available for sorting, safe storing, and distribution of food waste	C32	
		No full understanding of emerging technologies	C33	
		Loss of biocompounds caused by conventional extraction technology	C34	
		High energy consumption of technology	C35	
Economy	C4	High transport costs due to collection and processing of biomasses	C41	[51,54,63–65]
		High expenses related to the techniques utilized	C42	
		The shortage of investment in technologies/solutions	C43	
Government	C5	Lack of robust and detailed legal and regulatory foundation	C51	[54,66–68]
		The absence of agri-waste management digital platforms	C52	
		Lack of relevant incentive systems	C53	
Customer	C6	Less trust of consumers in safety of new products based on agricultural by-products	C61	[51,67,69]
		Little public awareness about agri-food waste valorization	C62	
		Obscure consumer acceptance due to changes in sensory quality	C63	

Stage 2. Evaluating the weights of challenges and elucidating relationships between them.

Step 3. Estimating the indicators' initial weights using FF-SWRAR.

In this step, the FF-SWRAR methodology was employed to determine initial weights of each challenge through assessment of three experts. Table 6 outlines the respective expertise levels of these three experts.

Table 6. Expertise levels of decision makers.

DM	Degree of Expertise	Influence of Assessment
E_1	HE	0.411
E_2	ME	0.295
E_3	ME	0.295

Clearly, "Government (C5)" emerges as the paramount dimension among the challenges to agri-food waste valorization, closely followed by the "Organization (C1)"dimension. Moreover, the initial pivotal challenges are "The absence of agri-waste management digital platforms (C52)", "Lack of relevant incentive systems (C53)", "Lack of robust and detailed legal and regulatory foundation (C51)", "Limited technological capabilities available for sorting, safe storing, and distribution of food waste (C32)", and "The absence of intermediary companies/departments collecting and directing wastes to specific points for processing (C13)".

Furthermore, Table 7 provides a comprehensive overview of the local weights and overall weights assigned to each challenge.

Table 7. Weights of dimensions and challenges.

Dimensions	Factors	Local Weights of Challenges	Overall Weights of Challenges
C1 0.246	C11	0.23	0.05
	C12	0.21	0.02
	C13	0.20	0.06
	C14	0.16	0.05
	C15	0.11	0.04
	C16	0.09	0.03
C2 0.123	C21	0.24	0.02
	C22	0.20	0.02
	C23	0.18	0.02
	C24	0.16	0.01
	C25	0.14	0.03
	C26	0.09	0.02
C3 0.186	C31	0.31	0.05
	C32	0.26	0.06
	C33	0.20	0.02
	C34	0.13	0.02
	C35	0.10	0.04
C4 0.102	C41	0.39	0.03
	C42	0.35	0.04
	C43	0.26	0.04
C5 0.252	C51	0.33	0.08
	C52	0.36	0.09
	C53	0.31	0.08
C6 0.091	C61	0.44	0.04
	C62	0.31	0.03
	C63	0.25	0.02

Step 4. Specifying the relationships between the indicators and adjusting weights using FF-DEMATEL-ISM.

In this step, the FF-DEMATEL-ISM was used to clarify interrelationships among challenges. Table 8 presents the identified causal relationships.

Table 8. Causal relationships of challenges.

Factors	C	D	C + D	Rank	D − C	Category
C11	1.28	0.01	1.286	2	−1.267	effect
C12	0.60	0.09	0.692	8	−0.514	effect
C13	0.77	0.11	0.885	6	−0.657	effect
C14	0.32	0.36	0.676	10	0.036	cause
C15	0.20	0.36	0.556	13	0.157	cause
C16	0.22	0.23	0.457	19	0.008	cause
C21	0.00	0.24	0.239	25	0.239	cause
C22	0.38	0.11	0.491	16	−0.264	effect
C23	0.41	0.12	0.532	15	−0.291	effect
C24	0.00	0.28	0.281	24	0.281	cause
C25	0.09	0.00	0.093	26	−0.093	effect
C26	0.35	0.00	0.346	23	−0.346	effect
C31	0.39	0.74	1.138	3	0.351	cause
C32	0.29	0.47	0.752	7	0.180	cause

Table 8. *Cont.*

Factors	C	D	C + D	Rank	D − C	Category
C33	0.29	0.39	0.688	9	0.100	cause
C34	0.42	0.00	0.420	20	−0.420	effect
C35	0.17	0.18	0.354	22	0.008	cause
C41	0.37	0.23	0.593	12	−0.141	effect
C42	0.39	0.16	0.551	14	−0.237	effect
C43	0.44	0.66	1.098	5	0.226	cause
C51	0.17	0.31	0.477	17	0.140	cause
C52	0.07	1.04	1.113	4	0.971	cause
C53	0.18	1.34	1.524	1	1.160	cause
C61	0.41	0.06	0.471	18	−0.343	effect
C62	0.00	0.60	0.599	11	0.599	cause
C63	0.00	0.40	0.404	21	0.404	cause

Table 9 illustrates the derived hierarchical structure.

Table 9. Hierarchical structure of challenges.

Level	Factors
1	C25
2	C11, C61
3	C13, C23, C26, C34
4	C12, C22, C35, C41, C42
5	C14, C16, C31, C32
6	C15, C33, C43, C51
7	C62, C63
8	C21, C24, C52, C53

Given the values of C−D in Table 8, the challenges have been categorized into cause-and-effect groups, as depicted in Figure 3. In the cause group, the most important challenges are “Lack of relevant incentive systems (C53)” and “The absence of agri-waste management digital platforms (C52)”. In the effect group, the most important challenges are “The absence of intermediary companies/departments collecting and directing wastes to specific points for processing (C13)” and “Poor logistical and infrastructural systems (C11)”. Based on C and D values, the prominence of the critical factors have been evaluated. The top five ranked challenges are “Lack of relevant incentive systems (C53)”, “Poor logistical and infrastructural systems (C11)”, “Lack of the most efficient and cost-effective extraction method for specific waste streams (C31)”, “Lack of robust and detailed legal and regulatory foundation (C51)”, and “The shortage of investment in technologies/solutions (C43)”.

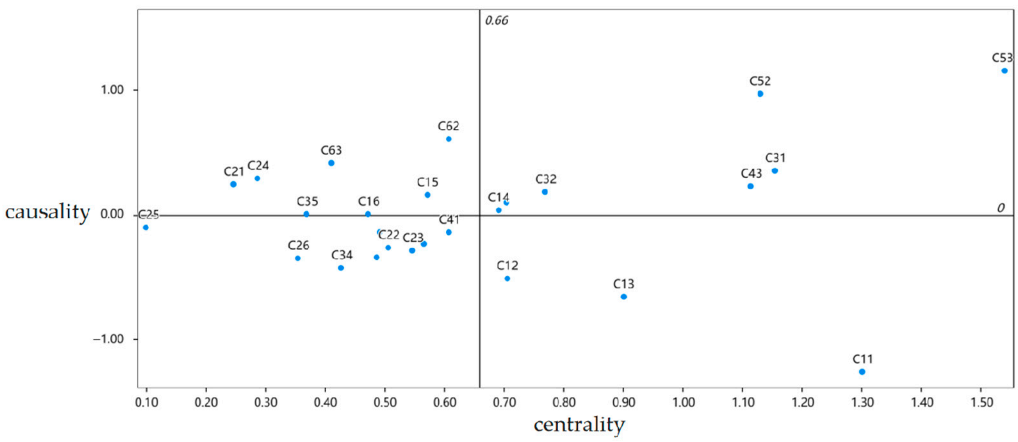

Figure 3. Centrality and causality of challenges.

After adjusting weights, the final most important challenges are "Lack of relevant incentive systems (C53)", followed by "The absence of agri-waste management digital platforms (C52)", "Poor logistical and infrastructural systems (C11)", "Lack of the most efficient and cost-effective extraction method for specific waste streams (C31)", and "The absence of intermediary companies/departments collecting and directing wastes to specific points for processing (C13)".

According to the analysis results of ISM (Table 9), the challenges of agri-food waste valorization can be divided into eight levels. The essential causal factors at the bottom level are "The region-dependent and seasonal availability of a waste stream (C21)", "High sensitivity of microorganisms to operating conditions (C24)", "Lack of relevant incentive systems (C53)", and "The absence of agri-waste management digital platforms (C52)".

Stage 3. Ranking the potential smart solutions to agri-food waste valorization.

Step 4. Identifying smart agri-food waste valorization solutions.

An in-depth investigation was conducted in the Web of Science databases, encompassing all existing publications about the utilization of smart technologies in agri-food waste valorization. Additionally, insights from professional experts were solicited. Consequently, a total of 18 innovative smart solutions were identified (Table 10).

Table 10. Smart solutions to agri-food waste valorization.

Codes	Solutions	References
S1	Employing AI to predict and classify the properties or characteristics of biowaste	[17,25,70–84]
S2	Utilizing AI to predict the volatile organic compounds (VOCs) and supply for waste materials	
S3	Improving transparency and safety of agri-food supply chains through contamination tracing and efficient food production system, e.g., IoT, blockchain, big data, RFID tags, GIS	
S4	Obtaining real-time and up-to-date digital information on crop growth, safety, and nutrition by UAVs, cloud computing, GIS	
S5	Using digital devices and platforms in rural agriculture as early warning system by using ICT, RFID tags, remote sensors	
S6	Cooperating between technology providers and adopters to advance sustainable agri-food supply chain management using remote sensors, weather forecasting systems, bio-stimulants	
S7	Integrating innovative agricultural technologies with farmers' traditional knowledge and constructing a knowledge-sharing platform	
S8	Facilitating connectivity and information sharing between supply chain members	
S9	Designing agri-food waste apps to link manufacturers, supermarkets, restaurants, and individual households	
S10	Searching and analyzing current databases to guide the selection of suitable agri-food waste valorization approach through AI	
S11	Identifying the exact parameters in the operational process based on BDA together with the sensors	
S12	Automatically identifying consumer needs to inform manufacturers and retailers utilizing text mining and information sharing platform	
S13	Applying IoT to monitor environmental parameters like temperature, dissolved oxygen and pH in the production process	
S14	Using intelligent algorithms for site selection and transportation path planning	
S15	Minimizing the carbon footprint of the entire supply chain by cloud computing	
S16	Implementing autonomous robots to reduce costs and improve operational professionalism	
S17	Increasing awareness of cybersecurity at all stages of the supply chain	
S18	Adopting digital twins to evaluate agricultural food waste quality and tailor supply chains to reduce losses	

Step 5. Prioritizing smart agri-food waste valorization solutions using FF-QFD.

As depicted in Table 11, the results of FF-QFD analysis reveal that in addressing current challenges, the most highly prioritized solutions are "Facilitating connectivity and information sharing between supply chain members (S8)", "Improving transparency and safety of agri-food supply chains through contamination tracing and efficient food production system e.g., IoT, Blockchain, Big Data, RFID tags, GIS (S3)", and "Utilizing artificial intelligence (AI) to predict the volatile organic compounds (VOCs) and supply for waste materials (S2)".

Table 11. Importance of smart solutions.

Codes	Absolute Importance	Rank
S1	0.016	10
S2	0.142	3
S3	0.154	2
S4	0.069	5
S5	0.042	6
S6	0.008	12
S7	0.020	9
S8	0.365	1
S9	0.099	4
S10	0.014	11
S11	0.002	17
S12	0.021	8
S13	0.003	14
S14	0.003	15
S15	0.004	13
S16	0.002	16
S17	0.002	18
S18	0.034	7

4.2. Discussion

This section focuses on the in-depth analysis of the aforementioned results. In terms of different dimensions of challenges, "Government (C5)" ranks the highest. Typically, the local government assumes a guiding role in a project, with its primary responsibility being to facilitate the participation of enterprises and the public. Particularly in the case of agri-food waste value-added initiatives, which necessitate substantial initial investments and yield returns over an extended duration, the role of governmental guidance and backing is imperative. In an empirical study, Xiang and Gao prove that government support exerts a remarkably positive influence on the sustainable development of the agricultural sector [85]. Notably, agricultural extension services and ecological subsidies, as key constituents of government support, contribute significantly to agricultural sustainability. Furthermore, through evolutionary games, some scholars demonstrate that it is crucial to enhance government's accountability and regulatory proficiency, robustly pursue technological advancements, and refine the incentive and disciplinary mechanisms to achieve both specialization and socialization of agricultural waste valorization [86]. The second important dimension is "Organization (C1)". Related business organizations constitute a significant driving force in the generation of waste, as well as the innovation and utilization of Industry 4.0 technologies [87]. Therefore, organizations serve as the actual main participants responsible for the valorization of agri-food waste. Should there be a lack of active engagement, an absence of instructions on agri-food waste valorization methods, and infrequent collaboration with other supply chain members, they are prone to adopting unscientific and unsystematic practices in managing agri-food waste, overlooking potential flaws in the logistical and infrastructural systems. Taking Kampala city for example, to achieve environmental, economic, and technical goals within urban settings, related organizations should carefully choose suitable technology-driven systems for agri-food waste valorization [88].

According to the Pareto principle [89], also known as the "80/20" rule, a deeper analysis has been conducted on the top 5 challenges out of a total of 26 identified challenges. The foremost challenge lies in "Lack of relevant incentive systems (C53)", which falls under the "cause" category. Actually, in Pakistan, Malaysia, and China, research finds that government incentives have a positive effect on the innovation of circular economy in small and medium enterprises [90]. Moreover, in Australia, lack of government incentive is a major barrier to developing a circular economy [91]. However, only a few countries, such as France, Italy, Austria, and Germany, have provided financial support in certain areas of agri-food waste valorization, but such financial support is only applicable to small-scale pilot projects and cannot be scaled up for large-scale promotion [92].

The following challenge is "The absence of agri-waste management digital platforms (C52)" belonging to the "cause" category. With regard to the governmental role, the traditional emphasis has predominantly centered on resources of financial wealth and administrative authority. However, other potential roles that governments could assume in fostering the development of agri-food waste valorization are often overlooked [93]. Specifically, there is a possibility for a government to leverage its central position within pivotal networks to gather advanced resources, thus creating a comprehensive digital platform to coordinate stakeholders and establish partnerships. Indeed, a key characteristic of the advancement of agri-food waste valorization lies in harnessing intricate networks of diverse actors, each possessing a range of requisite skills. In addition, the factor also highlights the necessity of using smart technology to address existing challenges.

The third important challenge is "Poor logistical and infrastructural systems (C11)", within the "effect" category. The factor is significantly influenced by numerous other variables, especially "The absence of relevant incentive systems (C53)", "The absence of agri-waste management digital platforms (C52)", and " The lack of the most efficient and cost-effective extraction method for specific waste streams (C31)". These contributory factors largely constrain the effectiveness of logistical and infrastructural systems in managing agricultural waste. Due to factors C53 and C31, numerous agricultural enterprises bear elevated risks when confronted with substantial investments in technology, thereby deterring them from proactive upgrading of their current infrastructural facilities [94]. In addition, the valorization of agri-food waste is not feasible solely through the efforts of a single enterprise, but requires the collaboration across the entire industry chain and even societal engagement. Hence, the absence of a unified digital management platform (C52) poses a significant obstacle in achieving seamless and standardized logistics systems.

The next challenge is "The lack of the most efficient and cost-effective extraction method for specific waste streams (C31)" under the "cause" category. Extracting effective substances from agricultural food waste is a decisive step in the valorization of agricultural food waste. Taking the extraction of cellulose as an example, isolating cellulose from biomass poses a significant challenge due to the recalcitrant nature of biomass, which inherently limits the accessibility of cellulose for value-adding applications [95]. Furthermore, the diverse range of agri-food sources containing cellulose renders it exceedingly difficult to devise a standardized extraction method capable of efficiently recovering cellulose across all types of sources. It is recommended that the forthcoming five years should be dedicated to exploring the innovative thermal extraction technologies, with a comprehensive techno-economic analysis conducted to thoroughly assess the feasibility and effectiveness of implementing these technologies in the extraction process of agricultural byproducts [96].

The fifth significant challenge, classified under the "effect" category, pertains to "The absence of intermediary companies/departments collecting and directing wastes to specific points for processing (C13)". In fact, as the waste bank is incapable of recycling the waste independently, the supply chain relies on a recycling factory to accomplish this task [97]. Besides the government dimension, the two most important influencing factors on the challenge are "Limited technological capabilities available for sorting, safe storing, and distribution of food waste (C32)" and "Rare cooperation between supply chain members in the process of agri-food waste valorization (C14)". The former underscores the substantial resource allocation to streamline the procurement of agri-food waste, thereby guaranteeing consistency, microbial safety, and superior quality for processing of waste, which once again demonstrates the necessity of government and social support [54]. The latter reason is aligned with a finding that the conversion of food waste into valuable products necessitates a concerted effort spanning the entire value chain and adopting a comprehensive food system viewpoint, which entails a profound understanding of the boundaries stemming from the subject's dynamic characteristics and interconnected dependencies [98].

The factors at the bottom level are fundamental factors. C21 and C24 are inherent attributes of the research subject. Specifically, the spatiotemporal distribution of agri-food waste and its high sensitivity to environment fundamentally impacts the cost and quality of biomass value-added processes. C53 and C52, in the "Government" dimension, play an external driving role in the valorization of agri-food waste, fully leveraging the aforementioned governmental prowess in resources and organization.

The subsequent discussion delves deeper into the top three solutions pertaining to smart technologies. Among these, the solution that emerges as the most effective is "Facilitating connectivity and information sharing between supply chain members by digital tools (S8)". Enhanced visibility and transparency within the supply chain empower members to identify and mitigate risks in a more efficient manner, thereby reducing the likelihood of disruption, particularly considering region-dependent and seasonal availability of the waste stream. Additionally, through swift exchange of information, supply chain members respond promptly to changes in market conditions in regard to obscure consumer preference. The solution also contributes to the establishment of a comprehensive agri-food waste management platform on a large scale. Among the digital tools, big-data management appears to be the most suitable for achieving S8, given its capability to facilitate the collection and sharing of diverse data types among organizations, ultimately enhancing the accuracy of outcomes [70]. The second important solution is "Improving transparency and safety of agri-food supply chains to customers through contamination tracing and efficient food production system e.g., IoT, Blockchain, RFID tags (S3)". Merely enhancing information exchange among enterprises within the supply chain is insufficient. It is essential to address the safety concerns of customers pertaining to new agri-food value-added products. Consequently, it becomes necessary to synchronize information derived from diverse production processes with customers to ensure their trust and satisfaction. In fact, the successful valorization of agri-food by-products heavily relies on robust traceability and rigorous quality monitoring in production and logistic system [29]. The third important solution lies in "Utilizing artificial intelligence (AI) to predict the volatile organic compounds (VOCs) (S2)". In practice, the variability in feedstock derived from biowaste significantly hinders the widespread utilization of value-added products. To overcome the difficulties, the valorization of agri-food waste has embraced artificial intelligence (AI), a novel approach, as a potential solution. According to diverse components of biomass, the overall dataset for training and testing in AI learning and the application of AI algorithms is diverse [19].

5. Conclusions

This study advances the existing literature by proposing solutions to the challenges of agri-food waste valorization considering smart technologies in Industry 4.0. Through a comprehensive review of the literature and insights from agricultural experts, challenges have been identified and subsequently categorized into six distinct dimensions: organization, environment, technology, economy, government, and customer. Then, a novel integrated MCDM approach including FFS and SWRAR-DEMATEL-ISM-QFD is employed to evaluate the challenges and potential solutions in the light of expert insights. Based on the findings of the FF-SWRAR, the "Government" dimension emerges as the most crucial, with a significant weight of 0.252, indicating its importance in addressing the challenges of agri-food waste valorization. According to the final weights of challenges, the top five most pivotal challenges are C53, C52, C11, C31, and C13. Next, the FF-DEMATEL-ISM method divides these challenges into cause and effect groups with eight levels, identifying the fundamental factors. Finally, FF-QFD prioritizes smart technology solutions in accordance with the varying weight of current challenges. Among these, three solutions stand out as the most significant, as follows: S8, S3 and S2.

5.1. Theoretical Implications

This study categorizes agri-food waste valorization challenges into macro-dimensions, offering perspectives for cross-sector researchers to comprehend the issue comprehensively. Within the context of sustainability and digitization, it preliminarily explores smart tech-based solutions, inspiring agricultural managers to adopt scientific methods and foster tech advancements. Furthermore, it introduces a novel MCDM framework, uncommon in agri-food waste evaluation, which can be adapted across domains, bolstering result reliability.

5.2. Practical Implications

Drawing from the research outcomes, this study presents several managerial implications that are expected to benefit government agencies and other stakeholders engaged in the management of agri-food waste. For government, it requires more initiative or knowledge to foster the development of agri-food waste valorization. The government should establish reasonable incentive mechanisms to ensure the service quality of fiscal funds in the field of agri-food waste valorization. Therefore, the government should seize the opportunity of applying and promoting agri-food waste valorization to improve risk management and performance evaluation in the agricultural supply chain. Beyond financial investments, the government needs to engage more stakeholders and jointly construct a technology-supported ecosystem for agri-food waste management. The digital waste management platform is expected to be positioned as a more solution-oriented approach, leveraging the integration of smart technologies in a practical and innovative manner to address environmental and social issues, thereby assisting governments and enterprises in making scientific decisions. For supply chain members, they should also enhance information disclosure and technological innovation. The strategic integration of upstream and downstream enterprises in the supply chain is the first step. Cooperation with upstream enterprises with resource aggregation can greatly reduce the risks related to raw material supply, while cooperation with downstream enterprises with first-hand market information can reduce the risks of demand uncertainty. Secondly, as the immense operational pressures and high costs associated with adopting advanced technologies may hinder enterprises in technological innovation, a potential lightweight mitigation approach involves the training of current employees to collaborate with digital technology providers that offer modular solutions. For smart technology providers, it is recommended to adopt a platform-based business model rather than a product-centric one. By adhering to established data standards, it becomes feasible for data to traverse the entire waste management value chain with the waste stream, thereby facilitating end-to-end digitization.

5.3. Limitations and Future Research

There are some limitations of this study. Firstly, despite a diligent review of the literature, encompassing all existing research on agri-food waste valorization remains challenging, limiting the comprehensiveness of identified challenges. Future studies should expand on empirical surveys to fill this gap. Secondly, smart technology solutions' practical implementation is complex, leading to limited detail in some proposed solutions. Further research should delve into precise smart technology applications for agri-food waste, with a more rigorous analysis. Lastly, while employing a Fermatean fuzzy framework, alternative uncertainty management methods warrant exploration and comparative analysis.

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ARTICLES FOR FACULTY MEMBERS

AUTOMATED SOLAR AND ELECTRIC COMPOST BINS FOR THE TOURISM AND FOOD & BEVERAGE (HOTEL) INDUSTRIES

Compositing machine design and automation: Agricultural and enviromental implications / Diaz-Quinto, S. F., Vilchez-Villaverde, F. C., Ramos-Porta, A. G. P., Beraun-Espiritu, M. M., Arellano-Vilchez, M. A., & Gamarra-Moreno, A. H.

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Compositing Machine Design and Automation:Agricultural and Enviromental Implications

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***Abstract*— Automated composting has proven to be a vital solution for the transformation of organic waste into high-quality compost, soil enrichment, and improved agricultural production. This innovation responds to the need to manage urban waste efficiently and mitigate emissions of polluting gases. The implementation of the VDI 2222 Methodology ensures a structured design in key stages, from preparation to compost collection, maximizing its efficiency and quality. The use of black box simulation modeling, backed by probability distributions and precise technology, is an advanced approach to improving the process. The combination of PID controllers and IoT technologies in the control system enables real-time monitoring and adjustment of temperature and humidity, optimizing the process and reducing the environmental footprint. In addition to improving soil quality and food production, this automation is aligned with sustainability goals. Static analysis provides crucial data for the successful design and construction of the composting machine. Efficient composting automation represents an important step towards the convergence of technology and agriculture, addressing current and future challenges in food production and environmental conservation.**

Keywords*— *Compositing, VDI 2222, PID, IoT technologies, sustainability.

I. Introduction

Compositing, a highly beneficial product for soil health, arises from a variety of wastes, including those of an organic nature. The abundance of these easily accessible resources is revealed in the daily disposal of waste that is placed in garbage bags. In this context, the compostage process emerges as a valuable opportunity, as it does not require fresh inputs, thus allowing the correct use of the huge amount of organic waste generated in urban areas. This transformation offers the possibility of redirecting a large proportion of the hundreds of tons of garbage currently produced, avoiding its destination in landfills and the subsequent emission of greenhouse gases. The automation of the composting process, framed by a machine designed specifically for this purpose, presents the opportunity to produce compost continuously and efficiently. This resulting nutrient-rich compost can play a key role as a fertilizer for both regional and national crops while contributing to mitigating the emission of gaseous pollutants and improving comprehensive waste management. This initiative would also provide significant support for soil and crop care, ultimately driving more food production, an objective of vital importance for food security [1-2].

In this context, our solution addresses the implementation of an automated process that ensures accurate control of temperature and humidity in each phase of the compostage. This monitoring and adjustment of critical parameters is carried out through a mobile application, which simplifies and speeds up the tasks of the end user. From notifications that alert to the start and end of the process to real-time monitoring of conditions, our proposal seeks to provide a comprehensive and practical experience for those involved in the automated composting process. In depth on each of the above-mentioned aspects, the benefits of composting, its potential for reducing emissions of polluting gases, improving waste management, and optimizing agricultural production through the use of high-quality compost will be analyzed in detail [3-4].

II. Materials and Methods

This project is based on the VDI 2222 Methodology, recognized for its structured and comprehensive approach to design, which is divided into four interrelated stages: Planning, Design, Design and Development. Following this consolidated methodology [5], the objective is to develop a composter that encompasses a set of six essential processes designed to optimize the production of high quality compost from organic waste and animal remains [6]. Likewise, in Fig. 1, a diagram indicating the process to be followed for the research is shown.

The operating stages of the composting machine include:

- Preparation of materials: Selection and conditioning of the organic components and debris required for the decomposition process [7].
- Material load: Controlled introduction of selected inputs into the composting system [8].

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- Mixing and airing: Movement and agitation of materials to ensure homogeneous distribution and adequate oxygenation, essential factors for efficient decomposition [9].
- Humidity control: Maintaining optimal humidity levels to promote microbial activity and material decomposition [10].
- Decomposition and ripening: The process of microbial decomposition that converts organic materials into mature and enriched compost [11].
- Compost collection: Extraction of finished compost ready for application as fertilizer on agricultural soils [12].

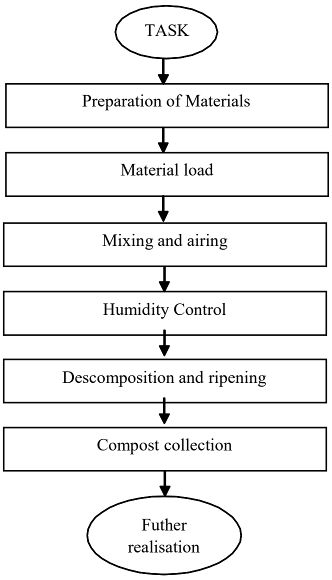

Fig. 1. VDI 2222

A. *Black Box*

The innovative approach in black box simulation modeling, supported by the use of probability distributions and automation, represents a precise step forward in the continuous improvement of the composting process from organic waste and animal manure in agricultural areas. By incorporating advanced statistical and technological principles, this helped raise the quality of the resulting compost, ultimately contributing to the enrichment of soils and progress towards more sustainable agricultural practices [15–16]. In Fig. 2. The black box of the composting machine can be seen.

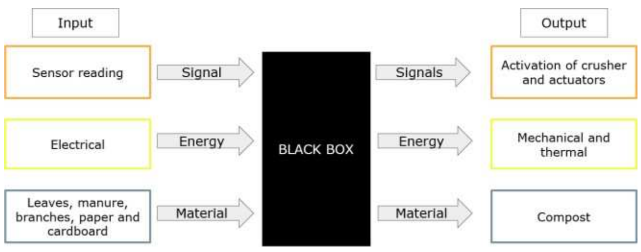

Fig. 2. Black Box structure

B. *Morphological Matrix*

The morphological matrix is a popular concept design tool. Although concept design methods based on morphological matrices are effective for concept scheme generation, which makes it difficult to determine the optimal concept design by combining these solution function principles [13-14]. The matrix is quantified so that each individual solution principle using decision variables and formulates the optimization problem [17] as shown in Fig. 2.

TABLE I. MORPHOLOGICAL MATRIX LEGEND

PARTIAL FUNCTIONS	SOLUTIONS			
	1 🔵	2 🟢	3 🟡	4 ⚫
Transport	Manual 🔵	Robot arm 🟢	Machinery 🟡	Conveyor belts ⚫
Power	Solar energy ⚫	Electric generator 🟡	General power 220v 🔵 🟢	Batteries
Dose	Manual	Hopper machine 🟡 🔵 🟢	Conveyor belts ⚫	Robot arm
Census	View	Sensors 🔵 🟡 🟢	Camera	Transducer ⚫
Crush	Blade 🟢 🔵	Hammer 🟡	Rollers	Chopped manual ⚫
Mixer	Palettes 🔵	Endless screw 🟡	Blender	Helical blades ⚫ 🟢
Aeration	Natural fan ⚫	Extractor 🔵 🟡 🟢	Mini air pump	Heater
Heating	Resistors 🔵 🟢	Burner	Cauldron 🟡	Solar ⚫
Humidification	Water Pump	Sprinkler 🟡	Manual ⚫	Humidifier 🔵 🟢
Process signal indicators	Alarm	Lights	Apps 🔵 ⚫ 🟢	Screens 🟡
Emptying	Manual	Helical blades ⚫ 🟢	Conveyor belts	Gravity 🟡 🔵
Process and action	ESP 32 ⚫ 🟢	Raspberry	PLC 🟡 🔵	PICs
Store	Sacks ⚫ 🟢	Boxes 🔵	Barres 🟡	Hopper machine

From the combination results, 4 solution concepts were determined as shown in TABLE II.

TABLE II. SOLUTION LEGEND BY COLOR

Color	Solution
Blue 🔵	S1
Green 🟢	S2
Yellow 🟡	S3
Black ⚫	S4

- S1: 1.1 – 2.3 – 3.2 – 4.2 – 5.1 – 6.1 – 7.2– 8.1 – 9.4 –10.3 – 11.4 –12.3 – 13.2
- S2: 1.2 – 2.3 – 3.2 – 4.2 – 5.1 – 6.4 – 7.2– 8.1 – 9.4 –10.3 – 11.2 –12.1 – 13.1
- S3: 1.3 – 2.2 – 3.2 – 4.2 – 5.2 – 6.2 – 7.2– 8.3 – 9.2 –10.4 – 11.4 –12.3 – 13.3
- S4: 1.4 – 2.1 – 3.3 – 4.4 – 5.4 – 6.4 – 7.1– 8.4 – 9.3 –10.3 – 11.2 –12.1 – 13.1

After acquiring the four resolution approaches, a modeling examination will be carried out to facilitate the selection and confirmation of the most efficient design in order to achieve the optimal solution.

C. Mathematical Calculations

A mathematical analysis of the compostage was carried out and the following results were obtained.

Caluculations of cylinder dimensions:

Data obtained:

$m = 30kg$

$\rho_{material} = 8000kg$

$\rho_{content} = 700kg$

$Ø = 1m$

Used formulas:

$$V_{product} = \frac{m}{p} \quad (1)$$

$$V_{recipiente} = V_{total\ product} * \frac{100\%}{6\%} \quad (2)$$

$$H = \frac{V_{container}}{\pi * r^2} \quad (3)$$

Volume calculation:

$$V_{content} = \frac{30\ kg}{700\frac{kg}{m^3}} = 0.0428m^3$$

$$V_{material} = \frac{30\ kg}{8000\frac{kg}{m^3}} = 0.00375m^3$$

$$V_{total\ product} = 0.04617m^3$$

$$V_{container} = V_{total\ product} * \frac{100\%}{6\%} = 0.7695\ m^3$$

Height calculation:

$$h = \frac{V_{container}}{\pi * r^2} = 0.9797\ m$$

The results obtained in the calculations of cylinder dimensions and other parameters are essential for the successful design and construction of the automated composting machine. These calculations provide critical information on how the machine should be designed and configured to ensure its efficient and safe operation. The benefits of the results obtained are described below,

Results of the calculations:

Optimal rotation speed = 20RPM

*Torque required for compost = 264.6 N*m*

Axis diameter = 45mm

Tangential speed = $0.047\frac{m}{s}$

Length of the stick = 0.036 m

Slate width = $0.0026\ m^2$

Centrifugal force by stick = 0.037 N

Number of sticks = 7 palas

Critical axle speed = $22.17\ \frac{m}{s}$

Minimum axle diameter =39.6mm

Maximum axle cutting effort =52.3 MPa

Axis safety factor = 4.8

Maximum cutting effort on the sticks = 6.3MPa

D. Control System

The project focuses on the design of a control system that combines the ESP32 controller and PID technology to optimize environmental factors in the compostage process. This will be achieved through the regulation of temperature and humidity at the different stages of the process, and real-time information will be provided to the user through an Android app. Wi-Fi connectivity will enable effective communication between the controller and the application, facilitating remote monitoring and adjustment of the compostage process parameters, as shown in Fig.3.

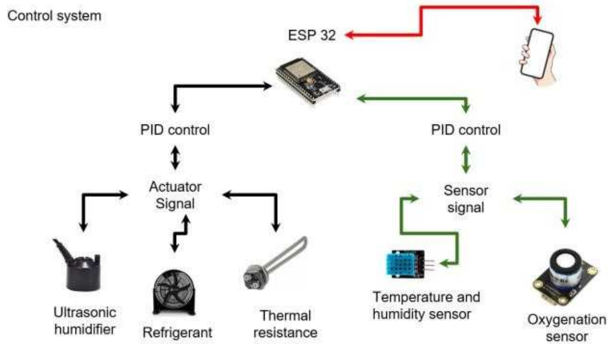

Fig. 3. Control system diagram

The materials to be used for the construction of the control system are shown in TABLE III.

TABLE III. CONTROL MATERIALS

Materials	Quantity
JGA25-370 Electric Gear Motor	1
ESP32 Arduino based controller with Wi-Fi	1
SHT31 Humidity and temperature sensor	1

E. Power System

This will allow the engine to be driven by running the entire mixing and crushing system, as well as controlling the energy that will be supplied to the electronic elements such as the controller and sensors. It will also feed the actuators responsible for regulating the environmental parameters of the compostage process, as shown in Fig.4.

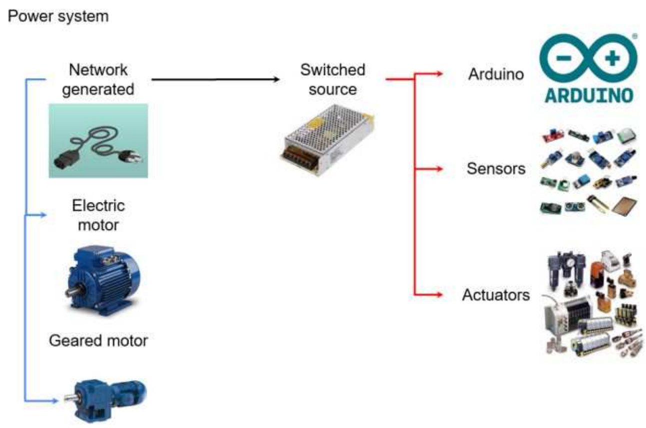

Fig. 4. Power System

The materials to be used for the construction of the power system are shown in TABLE IV.

TABLE IV. MATERIALS COMPOSTAGE

Materials	Quantity
1 HP three-phase motor.	1
2 HP three-phase motor.	1
Step Down Transformer 220v to 12v	1
1N4007 rectifier diode	4
LM7805 Voltage Regulator	1
LM7812 Voltage Regulator	1
Capacitor 1500 uF	1
14 AWG wire (5 meters)	3
Three Phase Contactor 40A	3
Three Phase Relay 40A	1
Three-phase thermomagnetic switch 40A	1
Single-phase thermomagnetic switch 40A	1

F. Mechanical design

The mechanical automation system in organic compostage aims to boost sustainability and productivity in agricultural areas by creating an efficient and controlled process that transforms organic waste into valuable compost for soil improvement and food production. Fig. 5 shows the mechanical design used by the Autodesk Software inventor.

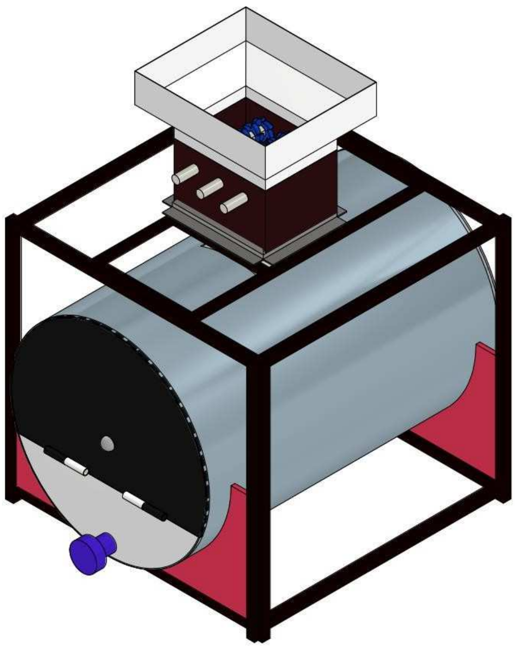

Fig. 5. Mechanical design

The materials to be used for the construction of the mechanical structure are shown in TABLE V.

TABLE V. MECHANICAL EQUIPMENT

Materials	Quantity
Stainless steel weldable round bar A276 C-304	1
Stainless steel smooth iron C-304/2B	1
Stainless steel weldable round bar A276 C-304	2

III. RESULTS

A static analysis was carried out for the purpose of evaluating the physical stress and stress levels of the composting machine, in order to determine its ability to withstand a load above 8000 N and with a torque greater than 1000 N.cm in the middle of the axles of the pallet. The results obtained from this analysis revealed that the machine is capable of supporting the load without presenting difficulties related to weight; however, in the part of the cylindrical lid, a deformation occurred due to the torsion that it presents in the middle part. For a more detailed view of the results, see Fig. 6.

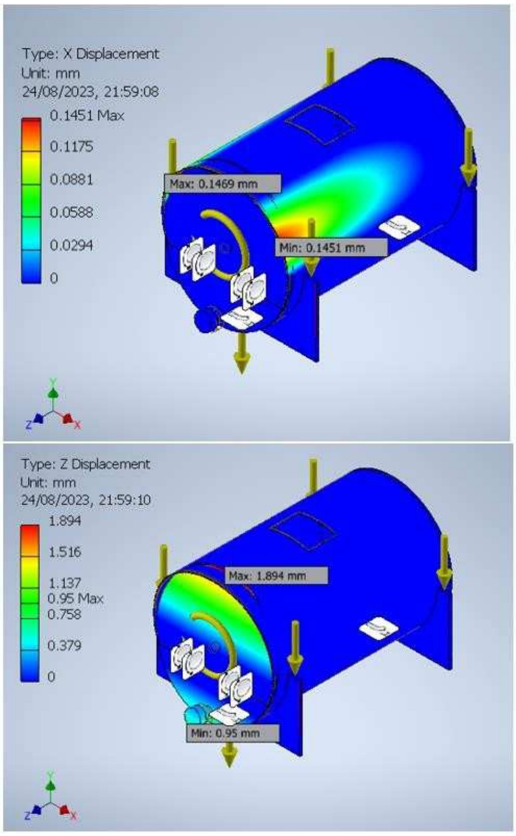

Fig. 6. Static analysis of the part of the process

In addition, the final results of the composter were obtained where the total weight of the machine exceeds 10000 N, and torsions greater than 1000 N.cm in the shafts of the shredder where the organic material was placed, the machine would have stainless materials so that it would not be subject to corrosion and facilitate its cleaning, in addition it would allow the acceleration of the final product as shown in Fig. 7.

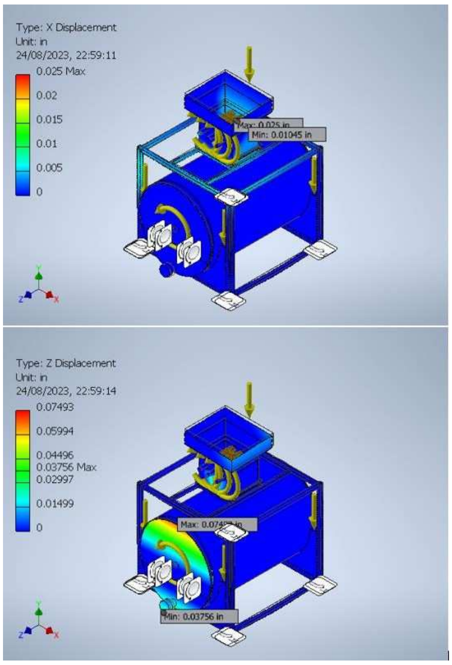

Fig. 7. Static analysis of the composting machine

Finally, these results provide essential information for designing, constructing and operating an efficient and secure automated composting machine. In addition, the calculations contribute to the optimization of the composting process, ensuring the quality of the produced compost and supporting the sustainability and productivity objectives in agricultural areas. The following Fig. 8 shows the results of the composting created

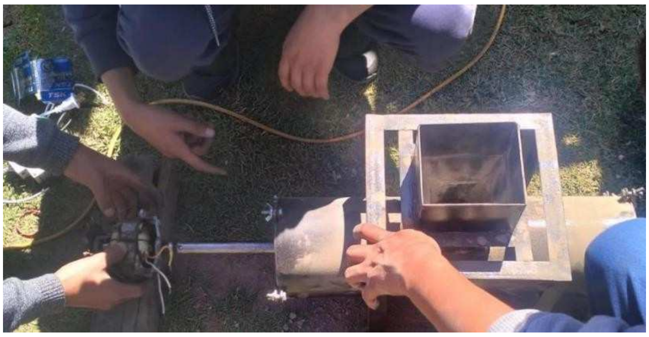

Fig. 8. Construction of the composting machine

IV. Discussion

Automation in composting presents a key solution for the efficient transformation of organic waste, although it faces significant challenges. To improve the management of critical parameters, further research into advanced sensors and control algorithms that can optimize the calibration and control of automated systems is recommended. Additionally, the implementation of technologies such as PID controllers and IoT can be made more accessible through training programs and financial support for farmers, encouraging a smoother transition to automated methods. In environmental terms, the discussion should highlight how the improved efficiency of automated composting can reduce greenhouse gas emissions and contribute to sustainable waste management. It is also suggested to investigate more sustainable materials for the construction of composting machines, promoting eco-friendly practices

V. Conclusion.

It was examined how the implementation of mechanical and technological systems in the composting process had had a significant impact in several aspects. From the importance of composting as a valuable method to have transformed organic waste into rich nutrients for the soil to the need to have optimized this process through automation, the relevance of this practice to have addressed environmental and agricultural challenges was highlighted. Automation has offered the possibility of regulating critical factors, such as temperature, humidity, and material mixing, with precision and consistency.

It had been explored how the implementation of control systems based on simulation models, such as the use of PID controllers and the integration of IoT technologies, had led to more efficient management of the composting process. The ability to monitor and adjust parameters in real time contributed to obtaining higher-quality compost while reducing the environmental footprint by minimizing the emission of greenhouse gases and unpleasant odors. Taken together, this efficient automation approach to organic composting had not only the potential to improve soil quality and increase food production but was also aligned with broader goals of sustainability and responsible resource management. The combination of advanced techniques, such as systems modeling and wireless communication, with practical application in agricultural areas has promised a more resilient and sustainable future for agriculture and the environment.

Ultimately, efficient automation of organic composting represented a significant step forward in the convergence between technology and agriculture, offering innovative solutions to address current and future challenges in food production and environmental conservation

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ARTICLES FOR FACULTY MEMBERS

AUTOMATED SOLAR AND ELECTRIC COMPOST BINS FOR THE TOURISM AND FOOD & BEVERAGE (HOTEL) INDUSTRIES

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EMPIRICAL ARTICLE

Humans and/or robots? Tourists' preferences towards the humans–robots mix in the service delivery system

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Abstract

This paper investigates tourists' preferences toward the humans-robots ratio in the service delivery systems of tourism and hospitality companies and the factors that shape them. The sample includes 1537 respondents from nearly 100 countries. The findings show that a higher preferred share of robots is positively associated with the perceived emotional skills of robots, their perceived usefulness in the tourism/hospitality context, perceived robotic service expectations, attitudes towards robots in general, and the male gender. On the other side, it is negatively associated with the perceived disadvantages of robots compared to human servers and the household size of respondents.

Keywords Robots · Humans–robots ratio · Tourism · Hospitality · Service delivery system

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1 Introduction

1.1 Rationale

In March 2015, the first robotised hotel (Henn na hotel in Nagasaki, Japan) was opened. It epitomised a revolution in the hospitality industry because it was equipped with 243 robots that provided service to customers (Hertzfeld 2019). Henn na hotel introduced a robotic service delivery system (Seyitoğlu and Ivanov 2020), in which robots implemented all front-of-house and the majority of back-of-house activities in the hotel. Other hospitality companies in the world were more conservative, introducing much fewer robots in their operations (e.g., one room service delivery robot in some hotels or a few robotic waiters in some restaurants). These companies relied on their human staff, using robots in a supporting role in their service delivery systems. In January 2019, the managers of Henn na hotel announced they turned off nearly half of the robots because they allegedly made the work of employees harder, rather than easier and due to the large number of complaints from customers and employees (Hertzfeld 2019).

The case of Henn na hotel raises the question: *How much automation in tourism and hospitality is too much automation*? This is a very broad question that cannot be answered in a single article because it needs to be addressed from the viewpoints of the various stakeholders of tourism and hospitality companies (tourists, employees, managers, owners, suppliers, intermediaries, local residents, etc.), consider the wide scope of automation technologies (robots, chatbots, kiosks, virtual/augmented/mixed reality, etc.), tourism and hospitality service settings (hotel, restaurant, bar, airport, etc.), and the breadth and diversity of front-of-house and back-of-house tasks that have the potential to be automated. This paper tries to partially answer the above question by looking at the perspective of the tourists regarding the use of robots in the front-of-house tasks in different tourism and hospitality contexts. More specifically, it looks at tourists' preferences towards the humans-robots mix in the service delivery systems of tourism and hospitality companies and the factors that form them.

The robot first came to prominence in science fiction, being invented as a word and concept in 1920 (NPR 2011); it came to supplant a great deal of labour after World War Two in industry and, in recent years, has been increasingly utilised in the service sector (Wirtz et al. 2018) and more recently in tourism and hospitality (Seyitoğlu and Ivanov 2020; Ivanov and Webster 2020; Kwak et al. 2021; Belanche et al. 2021a; Abou-Shouk et al. 2021). The demographic, environmental, and technological realities have worked in ways to encourage the greater use of robots in services. Even before the COVID-19 pandemic, the shrinking of the available labour force in developed countries has worked in ways to encourage employers to replace their workforce with automation (Webster 2021), including in tourism and hospitality (Webster and Ivanov 2020). The pandemic created an environment conducive to using technology to avoid humans touching and infecting each other (Seyitoğlu and Ivanov 2021). However, the current consumer has some concerns about using service robots since robophobes and robophiles have opposing perceptions of robots (Webster and Ivanov 2021a). Hence, there is a confluence of forces that influence the incorporation of robots into the service environment, some working in ways to encourage the increased use of robots and some working in ways to oppose the increasing use of robots in the labour force. While there is a great deal of evidence that tourism and hospitality companies are increasingly using automation technology to improve service, cut costs, and enhance the customer experience (Belanche et al. 2021a; Seyitoğlu et al. 2021), the service environment is unlikely to be fully automated by robots soon. Companies will likely use a mix of robots and human employees that will collaborate in the service delivery process. Some companies will rely on more robots while others—will rely on more human employees. This paper is the first one focusing on the tourists' perceptions about this humans-robots mix in the labour force of tourism and hospitality companies and the factors that shape them.

The topic is important because the use of robots in the service delivery systems of tourism and hospitality companies influences the perceived service quality (Chiang and Trimi 2020) and tourists' experience (Tuomi et al. 2021). Thus, knowing tourists' preferences towards the humans-robots ratio would allow companies to use the optimal number of robots in their service delivery systems and avoid the 'too much automation' phenomenon experienced at the Henn na hotel and mentioned earlier. This is especially important in hospitality, where the intimate and interactive relationship between service providers and consumers (Kandampully and Duddy 2001) and the politeness and empathy in the service delivery process (Marković et al. 2013) are vital for the tourists' experience. Moreover, knowing which factors shape tourists' preferences toward the humans-robots mix and what clusters of customers exist based on these preferences would allow tourism and hospitality companies to design the appropriate service delivery system for their target market and to develop appropriate strategies to communicate it to their customers.

1.2 Aim and objectives

The purpose of this paper is to evaluate tourists' preferences toward the humans-robots mix (ratio) in the service delivery systems of tourism and hospitality companies. Specifically, it aims to: (a) assess tourists' preferences towards the share of robots and human employees in the delivery of different tourism and hospitality services; (b) evaluate the role of various factors on the tourists' preferences, and (c) identify the existence of diverse groups of tourists based on their preferences towards the humans-robots ratio in the service delivery systems of tourism and hospitality companies.

The rest of the paper is organised as follows. The following section provides a focused literature review and develops the hypotheses. Section 3 presents the methodology. Section 4 elaborates on the results, while Sect. 5 summarises the paper's contribution, discusses the theoretical and managerial implications, addresses the limitations, formulates directions for future research, and concludes the article.

2 Literature review

2.1 Service delivery systems of tourism and hospitality companies

The service delivery system is based on companies' service design and shapes the service experiences and organisational structures (Avlonitis and Hsuan 2017). It includes organisational structure, consumers, processes, physical environment, technologies, human resources, and tasks (Paulisic et al. 2016). As one of the dimensions of the service strategy, the service delivery system is associated chiefly with how firms deliver their products or services to their customers (Ponsignon et al. 2011). The service delivery system comprises strategic design choices such as structural, infrastructural, and integration (Roth and Menor 2003). The structural choices refer to (i) physical elements: the used technologies and equipment, capacity management, facilities, etc., and (ii) the interfaces of service process: back-of-house operations, front-of-house operations, face-to-face or technology-mediated interactions. The infrastructural choices are related to the role of human resources in the service delivery system. Finally, the integration choices include internal integration between structural and infrastructural choices and external integration with the suppliers and the customers (Roth and Menor 2003). Therefore, it is evident that service delivery system design indicates servicescape (Bitner 1992), which is based on environmental psychology and is mainly associated with the relationship between human behaviour and physical environments (Lyu et al. 2017). Since the service delivery system plays a crucial role in shaping servicescape, a vast number of factors (e.g., technology, facilities, equipment, layout, the role of people, and service processes) should be considered in designing a service delivery system (Ponsignon et al. 2011). However, the role of each factor may vary as each service industry has different characteristics.

Since the tourism and hospitality industry is mainly related to the interaction between customers and service providers (Kandampully and Duddy 2001), service delivery systems rely on human service employees. Hence, the appearance, emotional intelligence, empathy, and efficiency of the service employees are crucial determinants of service quality, customer perceptions, and service experience (Seyitoğlu and Ivanov 2021). Furthermore, the positive host-tourist interaction in tourism leads to positive social interaction, intercultural attitude, development of friendships, and connectedness (Yilmaz and Tasci 2015). However, the recent technological development and the intervention of automation have influenced the service delivery systems of tourism and hospitality companies, and these influences may harm or make changes in the nature of tourists' experiences (Seyitoğlu and Ivanov 2021).

Considering service operations, using technological tools in tourism and hospitality service delivery systems may modify the characteristics of the companies' systems in terms of the costs, flexibility, capacity (Seyitoğlu and Ivanov 2020), the interactions between employees, tourists and the company (Koerten and Abbink 2022), etc. The interventions of technology may have both advantages and disadvantages for the companies. For example, service robots can provide novel and memorable experiences (Seyitoğlu and Ivanov 2022). Also, technology may increase the productivity and capacity of tourism and hospitality companies which may decrease costs and increase profits (Ivanov and Webster 2018). Especially during the pandemic, with the help of service robots, technology played a hygienic and protective role as physical contact between service providers and customers was eliminated (Lee and Lee 2020; Seyitoğlu and Ivanov 2021).

Service robots differ from other technological tools because they are face-to-face frontline agents interacting directly with customers, making technology a direct player instead of its link role such as software or computer in the service provision. Furthermore, robot-human and human-human interactions differ because there will be no or limited social and emotional intelligence in human-robot interactions (Belanche et al. 2020a). However, with the help of technological developments, robots' social and emotional intelligence could be developed, and although it would not still be a natural interaction between the human and the robot, more realistic interactions could be provided through service robots in the future. Therefore, the service delivery systems can be affected and re-structured in the tourism and hospitality services. However, the use of technology may reduce the flexibility of the service system and cause service failures and frustrations (Dabholkar and Spaid 2012). In addition, the high level of technology use may prevent interactions between tourists and employees in the tourism and hospitality service delivery systems (Seyitoğlu and Ivanov 2020).

The preceding discussion shows that the degree of technological intervention in tourism and hospitality service delivery systems is a critical subject that needs to be managed by tourism and hospitality companies. Therefore, several factors such as customer profile, expectations, the suitability of tasks to implementation by technology, the resources of companies (e.g., financial, physical), and the availability of automation technology should be considered while deciding the degree of using technology in service delivery systems in tourism and hospitality context (Seyitoğlu 2021).

2.2 Robots in the service delivery system of tourism and hospitality companies

Service robots have been increasingly utilised in various service delivery systems of industries, including tourism and hospitality. Service robots can make autonomous decisions in delivering services thanks to the use of data received by multiple sensors (Lu et al. 2019). Tourism and hospitality companies have adopted service robots to their service delivery systems to improve service quality, decrease costs, and provide new experiences to consumers (Belanche et al. 2021a; Seyitoğlu et al. 2021). In addition, the Covid-19 pandemic has accelerated this process since service robots enable contactless and safe services (Seyitoğlu et al. 2021).

On the one hand, service robots can be suitable for various tasks such as cleaning, washing dishes, lifting heavy items, provision of information, gardening services, hosting (host/hostess), processing card payments, issuing payment documents, busser/commis waiter tasks, supporting staff at the reception during group arrivals, distribution of promotional materials, Mise en place: the setup tasks before cooking for the tourism and hospitality companies (Ivanov et al. 2020; Tuomi et al. 2021; Seyitoğlu et al. 2021). On the other hand, they may not be appropriate for tasks requiring social and communication skills, such as implementing guests' special requests or handling complaints. Robots may not be suitable for jobs that require management skills and for more complex tasks such as cooking that require tacit knowledge and understanding of guests' emotions (Ivanov et al. 2020; Seyitoğlu et al. 2021; Belanche et al. 2021b).

Adopting service robots in tourism and hospitality companies is a significant subject. The managerial choice of the humans-robots mix in the service delivery system of tourism and hospitality companies is an especially critical issue. Regarding the humans-robots balance in service delivery systems, for example, Seyitoğlu and Ivanov (2020) defined three service delivery systems (robotic, human-based, and mixed) and analysed their advantages, disadvantages, requirements, and potential target markets. A recent empirical study on restaurants (Seyitoğlu et al. 2021) demonstrates that human-robot collaboration (mixed service delivery system) is the most suitable service delivery system as it makes up for the disadvantages of robots with the advantages of human employees and vice versa.

Van Doorn et al. (2017) proposed a typology of service delivery systems depending on the degree of automated social presence and human social presence in service environments. For instance, while the first system refers to the system in which service frontline experiences are low on both automated and human social presence, the second encompasses service frontline experiences with high human social presence but no or low automated social presence. Service frontline experiences high automated social presence, but low human social presence is emphasised in the third typology. Finally, the fourth typology represents the combination of high human and high automated social presence (van Doorn et al. 2017). Finally, by the study of Wirtz et al. (2018), a framework was developed based on the characteristics of the tasks (i.e., simple, complex, cognitive-analytical, emotional-social) and customer needs and desires. Therefore, human-delivered, robot-delivered, and human-robot team delivered service delivery systems were presented (Wirtz et al. 2018).

In addition, the knowledge of customer expectations may be helpful in the degree of robot adaptation in tourism and hospitality tasks because for successful market positioning, knowing the customer expectations is vital (Seyitoğlu 2021). Furthermore, in the (post-) pandemic epoch, the use of service robots in tourism and hospitality companies may be widespread because consumers may be more concerned about their safety while receiving services (Zeng et al. 2020). Hence, service robots may gain a strategic significance for the service delivery systems of tourism and hospitality firms in the future. In this vein, service robots may provoke a transformation in the tourism and hospitality service delivery systems.

2.3 Hypotheses development

This paper looks at the drivers of tourists' preferences towards the humans-robots mix in the service delivery systems of tourism and hospitality companies. Figure 1 visually depicts the factors elaborated in the paper. The customer acceptance and

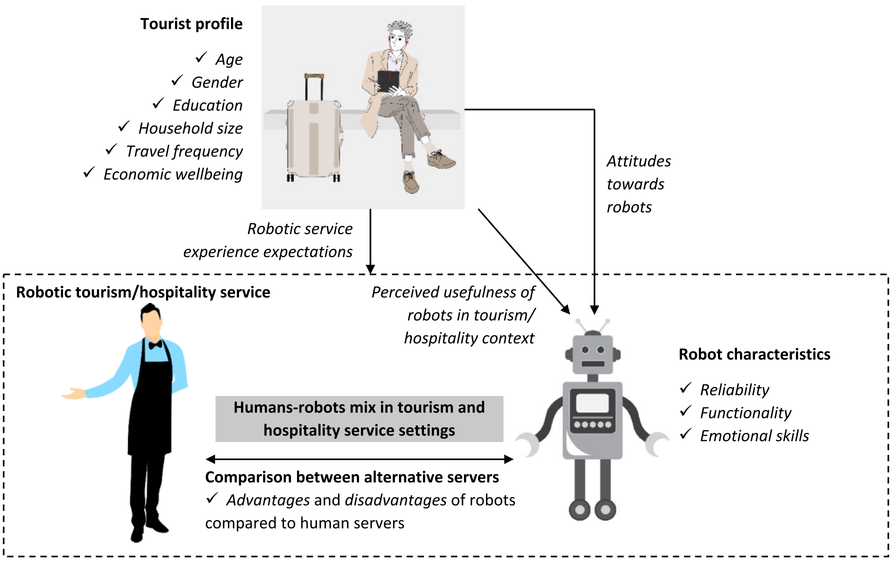

Fig. 1 Drivers of the humans-robots mix in the service delivery systems of tourism and hospitality companies

preferences of service robots have been studied from different perspectives in the literature. In this regard, the robots' functional and social-emotional requirements (humanoid communication skills, problem-solving skills etc.) are stressed among the significant ones that determine the customer preferences of service robots (Wirtz et al. 2018). Furthermore, robots' reliability (Cha 2020) and usefulness (McLean et al. 2020; Abou-Shouk et al. 2021) are also regarded as essential elements playing vital roles in customers' attitudes toward service robots. From the customer side, customer characteristics such as expectations (Ivanov et al. 2018a), attitudes and profiles (e.g., gender, age, personality traits, and culture) are also emphasised as crucial elements that influence consumers' preferences for service robots (Belanche et al. 2020b). Therefore, various variables such as robot reliability, robot functionality, robot usefulness, tourist attitudes, profile, and expectations shape tourists' preferences toward service robots. However, no study investigating the role of these elements on the tourists' preferences towards the share of robots in the service delivery system is found in the literature. Thus, to fill this void in the extant literature, this study includes these variables and investigates the mentioned relationships in the tourism and hospitality context.

2.3.1 Robot characteristics

Robot characteristics such as reliability (Cha 2020), functionality (McLean et al. 2020; Abou-Shouk et al. 2021) and emotional skills (Seyitoğlu et al. 2021; Stock-Homburg 2022) influence the customer perceptions of the use of robots in tourism and hospitality services. Previous studies have shown that perceived service robot reliability is positively associated with the perceived appropriateness of robot use in passenger tourist transport (Webster and Ivanov 2021b). In the restaurant context, the literature shows that when consumers feel that service robots are reliable, they are more inclined to use them (Cha 2020). Furthermore, Chiang and Trimi (2020) revealed that reliability is a priority for robots' service quality perceptions of customers. In this aspect, when robots provide a reliable service, tourists might be more willing to accept a greater share of robotic servers in the service delivery systems of tourism and hospitality companies.

On the other side, functionality is a key technical characteristic of service robots because it determines whether they would be capable of providing the service. Tussyadiah et al. (2017) found that the functionality of autonomous vehicles is positively linked to the use intentions of tourists. Furthermore, recent studies (McLean et al. 2020; Abou-Shouk et al. 2021) demonstrate a significant link between the perceived functionality of service robots and customers' attitudes. According to Lin and Mattila (2021), the functional benefits of service robots have a significant positive direct effect on consumer attitudes towards service robots in hotels. Additionally, when tourists see robots as functional, they would be more convinced that the robots would properly implement their assigned tasks and might accept more robots in the service delivery system.

Finally, robots' emotional skills determine human-robot interactions, use intentions, and actual use of robots in various service contexts (Seyitoğlu et al. 2021; Stock-Homburg 2022). In addition, emotions are an integral part of tourism and hospitality services (Ali et al. 2016; Marques et al. 2018) because tourism is often perceived as 'people's business' where people serve people. Customers expect positive emotions in their tourism experiences. Hence, customers expect robots to have emotional skills (Chuah and Yu 2021). If customers consider that robots have sufficient emotional skills, they would be more willing to accept them in the service delivery systems of tourism and hospitality companies.

Though these characteristics mentioned above of service robots are crucial in customer perceptions of the use of robots in tourism and hospitality services, no study investigating the relationship between these variables and tourist preferences towards robot-human ratio in service delivery systems was found in the current literature. Accordingly, the following hypotheses are formulated:

H1 Perceived service robot reliability is positively related to tourists' preferences towards the share of robots in the service delivery systems of tourism and hospitality companies.

H2 Perceived service robot functionality is positively related to tourists' preferences towards the share of robots in the service delivery systems of tourism and hospitality companies.

H3 Perceived emotional skills of service robots are positively related to tourists' preferences towards the share of robots in the service delivery systems of tourism and hospitality companies.

2.3.2 Alternative servers in the service delivery system

Robots and human employees are two alternative servers in the service delivery systems, each with advantages and disadvantages (Seyitoğlu et al. 2021). Their pros and cons play vital roles in tourists' preferences towards the share of robots in the service delivery systems of tourism and hospitality companies. For instance, Meidute-Kavaliauskiene et al. (2021) show that the perception of service robot advantages positively and significantly affects the intention to use service robots. Similarly, Ivanov et al. (2018a) reported that the perceived advantages of robots had a positive relationship with the attitudes towards the use of robots based on a sample of young Russian adults; the disadvantages had a negative effect that was eliminated when general attitudes towards robots were considered in the analysis. The same results were illustrated by Ivanov et al. (2018b) based on a sample of Iranian respondents. Additionally, Webster and Ivanov (2021b) found that robots' perceived advantages and disadvantages compared to human employees are, respectively, positively and negatively related to the perceived appropriateness of robot use in passenger transport. These results were partly supported by Webster and Ivanov (2022a, b), who found that perceived robot advantages were positively associated with the perceived appropriateness of robot application in museums and galleries. Therefore, the two hypotheses are:

H4 Perceived service robot advantages compared to human employees are positively related to tourists' preferences towards the share of robots in the service delivery systems of tourism and hospitality companies.

H5 Perceived service robot disadvantages compared to human employees are negatively related to tourists' preferences towards the share of robots in the service delivery systems of tourism and hospitality companies.

2.3.3 Robotic service experience

This paper focuses on the robotic service experience expectations similar to previous studies (Ivanov et al. 2018b; Ivanov and Webster 2021) due to the very small number of people who have actually experienced robotic services in the tourism and hospitality context. However, it has already been confirmed that robots can be used to create experiences for tourists (Tung and Au 2018), and their expectations about the service would motivate them to use it/buy it (Kytö et al. 2019). For example, Ivanov et al. (2018a) stress that robotic service experience expectations are positively associated with the attitude towards robotic service in hotels. In this vein, if tourists expect that robots would be beneficial for their travel experience, they would be more receptive to more robots in the service delivery systems of tourism and hospitality companies. Additionally, when tourists acknowledge robots as useful for their experience, they would be more likely to use them and prefer to be served by robots rather than humans. A recent study by de Kervenoael et al. (2020) showed that robots' usefulness is positively related to the perceived value of service robots, while Zhong et al. (2021) found that robot usefulness is positively associated with the attitudes toward robots in hotels. Consequently, the two hypotheses are developed as follows:

H6 Tourists' robotic service experience expectations are positively related to their preferences towards the share of robots in the service delivery systems of tourism and hospitality companies.

H7 Perceived service robot usefulness in the tourism/hospitality context is positively related to tourists' preferences towards the share of robots in the service delivery systems of tourism and hospitality companies.

2.3.4 Attitudes towards robots

The literature suggests that the attitudes toward robots are positively linked to the use intentions (McLean et al. 2020; Meidute-Kavaliauskiene et al. 2021; Molinillo et al. 2022) and the perceived appropriateness of robot use in tourism and hospitality context (Webster and Ivanov 2021b, 2022a). A recent study (Seyitoğlu et al. 2021) indicates that the valence of customer attitudes (positive or negative) determines customers' readiness to use service robots in restaurants. In addition, Webster and Ivanov (2022b) found that respondents with more positive attitudes toward robots preferred more robotic servers during events compared to respondents with more negative or neutral attitudes. Therefore, the literature clearly stresses the positive link between consumer attitudes and service robot use intentions. Consequently, we hypothesise that people with more positive attitudes toward service robots would be more receptive to a greater share of robots in the service delivery systems of tourism and hospitality companies. Formally, the hypothesis states:

H8 Tourists' attitude towards robots is positively related to their preferences towards the share of robots in the service delivery systems of tourism and hospitality companies.

2.3.5 Tourist profile

Characteristics of individuals can shape their perceptions and attitudes towards service robots although empirical findings are often mixed. For example, younger people have a more positive attitude towards service robots than older ones (Onorato 2018). The study of Reich and Eyssel (2013) on the general use of service robots also shows that the profile of consumers influences their perceptions—females have fewer positive attitudes and more significant anxiety toward service robots than males. Additionally, the authors found that respondents with an occupational background in technology or science and other non-social careers had more positive attitudes towards service robots than respondents who work or study in social areas (Reich and Eyssel 2013). At the same time, age and education did not change positive attitudes towards service robots.

Previous studies in tourism and hospitality literature have indicated that the profile of tourists shapes their perceptions of service robots. For example, Cha (2020) revealed that hedonically motivated consumer innovativeness and socially motivated consumer innovativeness positively affect attitude. However, the relationship between motivated consumer innovativeness and attitude differed among age groups. Thence, it can be implied that age can be considered a critical issue in consumers' attitudes and preferences toward service robots. Additionally, Ivanov et al. (2018a) found that males were more supportive of implementing robots in hotels, while Ivanov and Webster (2021) revealed that household size is positively related to the willingness to pay for robotic tourism and hospitality services. In addition, the hedonic and social elements of motivation contribute to the attitude and usage intentions of robot service restaurants; however, these relationships differ in terms of the income level of the customer groups (Kwak et al. 2021). Finally, people who travel more frequently are willing to pay less for robot-delivered services (Ivanov and Webster 2021). Travel frequency was also found to partially shape the perceptions of Iranians towards service robots in hotels (Ivanov et al. 2018b), but no such relationship was found for Russian respondents (Ivanov et al. 2018a). In this regard, it can be concluded from the extant literature that tourists' profile and characteristics may play significant roles in service robots' preferences of the share of robots in the service delivery systems of tourism and hospitality companies. Thus, the related hypotheses are:

H9.1 Gender shapes tourists' preferences towards the share of robots in the service delivery systems of tourism and hospitality companies.

H9.2 Age shapes tourists' preferences towards the share of robots in the service delivery systems of tourism and hospitality companies.

H9.3 Household size shapes tourists' preferences towards the share of robots in the service delivery systems of tourism and hospitality companies.

H9.4 Education shapes tourists' preferences towards the share of robots in the service delivery systems of tourism and hospitality companies.

H9.5 Economic wellbeing shapes tourists' preferences towards the share of robots in the service delivery systems of tourism and hospitality companies.

H9.6 Travel frequency shapes tourists' preferences towards the share of robots in the service delivery systems of tourism and hospitality companies.

2.3.6 Clusters

Tourists are not uniform in their perceptions of robots. For instance, Ivanov and Webster (2021) identified two clusters based on the willingness to pay for robot-delivered services, while Ivanov et al. (2018b) revealed the existence of two clusters of Iranian respondents based on their attitudes towards robots in hotels. Furthermore, Lee et al. (2021) investigated the underlying perceptions of the hotel guests' robot-using behaviours. They categorised the participants into cohesive groups showing similar characteristics. In line with the different demographic information and levels of perceptions, four clusters were identified as the ordinary, enthusiastic adopter, tech laggard, and value seeker. Finally, Zhong et al. (2022) implemented a cluster analysis to place guests into technology readiness index categories in this study. Four groups were revealed according to the clustering: paranoids, innovators, laggards, and sceptics. Hence, it is prominent from the current literature that as each individual may have different perspectives or attitudes towards a subject or experience, tourist segmentations are likely to occur, especially when the number of participants is higher. Consequently, we hypothesise that different clusters will exist based on tourists' preferences toward the humans-robots mix in the service delivery system:

H10 Different clusters of tourists exist based on their preferences towards the share of robots in the service delivery systems of tourism and hospitality companies.

3 Methodology

3.1 Research design and data collection

Between March 2018 and October 2019, a major online survey was fielded to learn about how the public perceives the use of robots in tourism and hospitality. The survey was developed first in English and later translated into 11 other languages to ensure a more inclusive and diverse pool of respondents. Native speakers of the languages translated the questionnaire to ensure that the translations were accurate and understandable to respondents. In addition, the respondents to the survey all had to self-identify that they were over the age of 18 so that no minors would be in the survey pool. The authors received permission from a major US university's IRB to disseminate the survey online through social media and email. The researchers disseminated the links to the weblink to the Qualtrics survey via their social media accounts, via emails to students/faculty, and via requests for the forwarding of the weblink to various collaborators throughout the world. A weakness of this methodology is that it is impossible to measure the response rate since it is unclear how many people throughout the world had received the link and chose not to take the survey.

3.2 Questionnaire

The key dependent variable in this analysis was the desired ratio of humans to robots. Respondents were asked to rate their desired ratio of humans to robots on a 7-point scale to operationalise this. The scale indicates on the lower end (1) "I prefer to be served only by robots" while on the other end (7) "I prefer to be served only by human employees." The middle (4) denoted "I prefer to be served by approximately an equal number of human employees and robots."

The respondents were then asked to indicate preferences towards the human employees-robots ratio in the following services/industries (Hotel, Room service, Restaurant, Bar, Travel agency, Tourist information centre, Rent-a-car, Airplane, Bus, Train, Ship, Airport, Bus station, Train station, Port, During an event such as a concert, congress, exhibition, and Museum/gallery). This question determines whether the customer's desired humans to robots ratio would change based on the tourism/hospitality service context.

In addition, the questionnaire included questions related to the perceptions of robot reliability and functionality (adapted and expanded from Tussyadiah et al. 2017), perceived usefulness of service robots in tourism (adapted and expanded from Venkatesh and Davis 2000), perceived advantages and disadvantages of robots compared to human employees, robotic service experience expectations, and perceived emotional skills of robots (adapted and expanded from Ivanov et al. 2018a). All these concepts were measured upon a seven-point level of agreement scale. Demographic data were collected as well.

3.3 Sample's characteristics

There were 1537 complete responses to the questions under consideration in this analysis. Table 1 illustrates the characteristics of the respondents. What is noteworthy is that the countries that are best represented in the survey, Bulgaria and the USA, stand out, since this is where the researchers are based, and it seems that their professional and personal contacts worked best to ensure a high response rate. Still, these two countries represent less than half of the respondents to the survey, allowing for nearly 100 other countries to be represented in the sample. The sample is well balanced in terms of gender. The respondents appear to be quite well-educated, young, and wealthy.

3.4 Data analysis

The descriptive analysis showed that the skewness and kurtosis values of all variables were within the range $[-1;+1]$ and that the sample size was sufficiently large (>500 respondents). Therefore, the empirical distribution of responses was treated as normal (George and Mallery 2019), which allowed the application of parametric tests (*t*-tests and ANOVA) for data analysis. Cluster analysis was implemented to identify groups of respondents based on their preferences towards the humans-robots ratio in the service delivery systems of tourism and hospitality companies. The number of respondents in the cluster analysis (1537) exceeded 90 times the number of variables in the segmentation base (17), which was much higher than the minimum ratio of 70 recommended by Dolnicar et al. (2014). Exploratory factor analysis and regression analysis were used as well.

Table 1 Sample's characteristics

	Total	Share	Number of respondents			Test statistic
			Cluster 1	Cluster 2	Cluster 3	
Gender						
Female	838	54.5	111	284	443	$\chi^2 = 38.264$ (df = 2, $p = 0.000$)
Male	699	45.5	179	210	310	
Age						
18–30	757	49.3	130	233	394	$\chi^2 = 13.510$ (df = 8, $p = 0.095$)
31–40	374	24.3	82	119	173	
41–50	229	14.9	39	73	117	
51–60	114	7.4	25	43	46	
61 +	63	4.1	14	26	23	
Household size						
1	174	11.3	38	53	83	$\chi^2 = 15.088$ (df = 10, $p = 0.129$)
2	352	22.9	79	106	167	
3	369	24.0	72	132	165	
4	361	23.5	59	117	185	
5	162	10.5	27	53	82	
6 or more	119	7.7	15	33	71	
Education						
Secondary or lower	213	13.9	35	62	116	$\chi^2 = 8.062$ (df = 6, $p = 0.233$)
2 year/Associate degree	102	6.6	18	33	51	
Bachelor	494	32.1	98	144	252	
Postgraduate (Master, Doctorate)	728	47.4	139	255	334	

Table 1 (continued)

	Total	Share	Number of respondents			Test statistic
			Cluster 1	Cluster 2	Cluster 3	
Economic wellbeing						
Much less wealthy than average for the country	45	2.9	5	19	21	$\chi^2 = 14.002$ (df = 12, $p = 0.301$)
Less wealthy than average for the country	99	6.4	15	35	49	
Slightly less wealthy than average for the country	163	10.6	23	54	86	
About the average for the country	500	32.5	91	154	255	
Slightly more wealthy than average for the country	447	29.1	93	149	205	
More wealthy than average for the country	226	14.7	47	65	114	
Much more wealthy than average for the country	57	3.7	16	18	23	
Travel frequency: times stayed in hotels during the last 12 months						
None	162	10.5	27	56	79	$\chi^2 = 10.025$ (df = 6, $p = 0.124$)
1–3 times	719	46.8	122	240	357	
4–6 times	366	23.8	69	109	188	
7 times or more	288	18.7	71	89	128	
Missing	2	0.1				

Table 1 (continued)

	Total	Share	Number of respondents			Test statistic
			Cluster 1	Cluster 2	Cluster 3	
Country of residence						
United States of America	385	25.0	59	134	192	$\chi^2 = 63.565$ (df = 32, $p = 0.001$)
Bulgaria	311	20.2	74	83	154	
China	71	4.6	14	15	42	
Taiwan	60	3.9	8	17	35	
United Kingdom	57	3.7	10	21	26	
India	54	3.5	10	19	25	
Turkey	45	2.9	12	13	20	
Italy	40	2.6	8	14	18	
Russian Federation	35	2.3	4	7	24	
Portugal	32	2.1	1	22	9	
Malaysia	29	1.9	5	6	18	
United Arab Emirates	25	1.6	4	8	13	
Brazil	22	1.4	4	8	10	
Germany	20	1.3	6	4	10	
France	19	1.2	4	6	9	
Spain	19	1.2	1	13	5	
Other (83 countries)	311	20.2	65	104	142	
Missing	2	0.1				

Table 1 (continued)

	Total	Share	Number of respondents			Test statistic
			Cluster 1	Cluster 2	Cluster 3	
Attitudes towards robots in general						
Mean	5.25	–	6.10	4.56	5.39	$F = 136.073$ ($p = 0.000$)
Standard deviation	1.411	–	1.071	1.587	1.166	
Total	**1537**	**100.0**	**290**	**494**	**753**	

Bold values indicating the total number of respondents and the number of respondents in each cluster

4 Results and discussion

4.1 The general picture

Table 2 presents the descriptive part of the results. The findings show that the respondents preferred to be served by slightly more human servers than robotic servers: all means were above the midpoint 4, reflecting the equal number of human employees and robots in the service delivery system. It is interesting to note that the mean humans-robots ratio was lowest (i.e. the share of robots is highest) for services with the shortest interaction between the service providers and the tourists, such as at train stations ($m = 4.25$), bus stations ($m = 4.26$), and room service ($m = 4.34$), or for services related to the provision of information which is mainly repetitive such as at tourist information centres ($m = 4.33$). Akdim et al. (2021) also underline that service robots are preferred when they provide quick service (e.g., in fast-food restaurants or roadside hotels). However, human employees are preferred in restaurants where customers want to socialise (e.g., traditional restaurants or fine dining restaurants) (Akdim et al. 2021).

For services with a strong social element, such as restaurants ($m = 5.06$) and bars ($m = 5.12$) (Seyitoğlu et al. 2021), respondents preferred a much higher share of humans than robots compared to other services, and the differences were all statistically significant at $p < 0.001$ (not reported on the table but available from the authors). These findings are consistent with the previous studies. For example, Seyitoğlu et al. (2021) uncovered that most restaurant patrons are willing to be served in a mixed service delivery system (in which service robots are used for some front-of-house operations) and a human-based service delivery system (in which human employees deliver all front-of-house operations, but robots may be used for some back-of-house operations).

4.2 Cluster analysis

The cluster analysis revealed the existence of three groups of respondents based on their preferences towards the humans-robots ratio in the tourism and hospitality services and service contexts listed in Table 2. Thus, H10 is supported. Cluster 1 ($n = 260$) included respondents that overwhelmingly preferred to be served by more robots than humans—means ranged from $m = 2.14$ (train stations) and $m = 3.51$ (bars). Unsurprisingly, they also had very positive attitudes towards robots ($m = 6.10$, see Table 1). This result echoes the findings of previous studies the attitudes toward service robots are strongly associated with the perceived appropriateness of robots with the tasks and use intentions (McLean et al. 2020; Webster and Ivanov 2021a; Meidute-Kavaliauskiene et al. 2021).

Cluster 2 respondents ($n = 494$) were on the other extreme and preferred mostly humans to robots in the service delivery—the mean responses ranged from $m = 5.84$ (tourist information centre) to $m = 6.38$ (restaurant). As a whole, the respondents in this group had neutral attitudes towards robots ($m = 4.56$). This cluster mostly

Table 2 Humans–robots ratio preferences: *t*-test and ANOVA

Sector	Total		*t*-test	ANOVA F-statistic						
	Mean	Standard deviation	Gender	Age	Household size	Education	Economic wellbeing	Travel frequency	Attitude	Cluster
Hotel	4.69	1.613	− 4.096***	1.165	0.667	3.828**	0.741	0.880	45.775***	1097.974***
Room service	4.34	1.785	− 1.237	1.003	0.932	1.419	2.338*	1.231	36.360***	960.694***
Restaurant	5.06	1.573	− 3.824***	1.651	1.181	1.753	1.102	0.336	34.577***	676.640***
Bar	5.12	1.566	− 3.817***	0.532	1.743	1.115	1.105	1.047	28.330***	528.260***
Travel agency	4.73	1.643	− 4.283***	1.957	1.559	1.490	1.046	0.544	35.820***	889.467***
Tourist information centre	4.33	1.717	− 3.204***	1.119	1.021	2.242	1.064	0.100	28.941***	755.344***
Rent-a-car	4.31	1.697	− 4.264***	0.727	1.643	1.149	2.567*	1.250	46.219***	1204.855***
Airplane	4.90	1.634	− 5.520***	2.188	0.931	1.040	2.219*	2.196	39.997***	761.989***
Bus	4.48	1.686	− 4.703***	0.760	1.070	0.876	2.327*	1.060	39.964***	1212.555***
Train	4.52	1.654	− 4.934***	1.247	3.147**	0.619	1.840	0.840	43.458***	1094.881***
Ship	4.82	1.571	− 4.709***	0.714	0.303	1.010	0.845	0.085	36.245***	959.909***
Airport	4.47	1.688	− 4.070***	0.830	1.495	1.034	2.190*	1.498	46.145***	1398.293***
Bus station	4.26	1.682	− 3.392***	1.072	2.585*	0.908	2.524*	0.732	40.533***	1285.736***
Train station	4.25	1.694	− 3.403***	1.363	3.272**	1.371	1.787	0.825	46.530***	1351.411***
Port	4.52	1.613	− 3.944***	2.185	1.293	1.575	2.509*	0.888	45.228***	1271.608***
During an event (e.g. concert, congress, exhibition)	4.72	1.601	− 4.208***	2.460*	0.995	0.852	1.985	1.338	29.426***	735.033***
Museum/gallery	4.45	1.708	− 3.532***	1.877	0.977	0.517	0.746	1.389	28.246***	742.356***

Question: indicate your preferences towards the human employees-robots ratio in the following services/industries

Humans-robots ratio coding: 1—I prefer to be served only by robots, 4—I prefer to be served by approximately equal number of human employees and robots, 7—I prefer to be served only by human employees;

***Significant at $p < 0.001$, **significant at $p < 0.01$, *significant at $p < 0.05$

prefers humans in service delivery for the service environment, such as tourist information centres and restaurants, because these tasks require personalised services. The recent studies (Ivanov et al. 2020; Seyitoğlu et al. 2021; Belanche et al. 2021b) also emphasise that service robots may not be advantageous for the tasks requiring humanoid characteristics such as social skills, communication, and emotion to fulfil customers' needs for more personalised services.

The third cluster was the largest one ($n = 753$), and respondents in it preferred an approximately equal number of humans and robots in the service delivery: min $m = 3.93$ (bus/train stations), max $m = 4.93$ (bar). All differences among clusters' responses were significant at $p < 0.001$ (see the last column in Table 2). The participants of a related study on restaurants (Seyitoğlu et al. 2021) also indicated that human-robot collaboration is the most suitable service delivery system because it provides both sides' (human and service robots) advantages in the service environments.

The characteristics of the clusters are presented in Table 1. Nearly 64% of Cluster 1 respondents were males, while 57.5% of Cluster 2 and 58.83% of Cluster 3 respondents were female, and the differences were statistically significant ($\chi^2 = 38.264$, df = 2, $p = 0.000$). This means that male respondents were more supportive of the use of robots in the service delivery systems of tourism and hospitality companies than females and accepted to be served by more robots than females did. These findings are consistent with Reich and Eyssel (2013)'s study, which revealed that males have more positive attitudes toward the use of service robots.

The literature supports that different clusters may exist regarding the perceptions of consumers towards the use of service robots in tourism and hospitality services in terms of willingness to pay for robots-delivered services (Ivanov and Webster 2021), attitudes towards service robots in hotels (Ivanov et al. 2018b), underlying perceptions of the hotel guests' robot-using behaviours (Lee et al. 2021), and placing guests into technology readiness index categories (Zhong et al. 2022). However, to the best of our awareness of the current literature, no study has yet investigated the clustering of consumers' preferences towards the humans-robots ratio in the tourism and hospitality literature.

4.3 Factors shaping the preferences towards the 'humans-robots' ratio

Table 2 presents the t-test and ANOVA results. They reveal that respondents' preferences towards the humans-robots ratio were largely shaped by respondents' gender (H9.1), attitude towards robots (H8) and cluster belongingness (elaborated in Sect. 4.2). All but one difference in the mean answers of respondent groups were statistically significant at $p < 0.001$. In general, males and people with more positive attitudes towards robots accepted more robots in the service delivery systems than females and people with negative attitudes towards robots. The age (H9.2), household size (H9.3), education (H9.4), economic wellbeing (H9.5) and travel frequency (H9.6) had no or little effect on the humans-robots ratio preferences.

The factor analysis results are presented in Tables 3, 4 and 5. As a whole, the extracted factors have high convergent validity because all Cronbach alpha values

Table 3 Factor analysis—humans-robots ratio preferences

Variable	Item loadings
Humans-robots ratio preferences ($\alpha = 0.968$, CR = 0.980, AVE = 66.447%)	
Hotel	0.851
Room service	0.803
Restaurant	0.766
Bar	0.721
Travel agency	0.809
Tourist information centre	0.775
Rent-a-car	0.843
Airplane	0.788
Bus	0.843
Train	0.834
Ship	0.828
Airport	0.864
Bus station	0.850
Train station	0.857
Port	0.857
During an event (e.g. concert, congress, exhibition)	0.779
Museum/gallery	0.772

Extraction method: principal component analysis, rotation method: varimax with Kaiser Normalization

Coding: 1—I prefer to be served only by robots, 4—I prefer to be served by approximately equal number of human employees and robots, 7—I prefer to be served only by human employees

***Significant at $p < 0.001$

are above 0.7 (min = 0.732, max = 0.968), all composite reliability values are above 0.8 (min = 0.868, max = 0.980), and all but one factor loadings are above 0.7 (see Tables 3 and 4). Table 5 shows that the constructs have a high discriminant validity because all square roots of the extracted variances of the constructs (diagonal values) are higher than the respective bivariate correlations with the other constructs (the values below the diagonal).

Table 6 elaborates the regression analysis results. Five regression models were developed with the humans-robots ratio preferences as the dependent variable. Model 1 included as independent variables only the respondents' perceptions of the characteristics of robots (reliability, functionality and emotional skills). The next models added as independent variables the perceptions towards the advantages and disadvantages of service robots compared to human employees (Model 2), the robotic service experience expectations and robots' usefulness in tourism and hospitality context (Model 3), the attitudes towards robots (Models 4), and the tourist profile (Model 5). As a whole, the five models have good explanatory power and explain between 22.6% (Model 1) and 39.1% (Model 5) of the variation of the dependent variable. No multicollinearity was observed in any of the

Table 4 Factor analysis—other constructs

Variable	Mean	Standard deviation	Item loadings
Perceived robot reliability[a] ($\alpha = 0.750$, CR = 0.900, AVE = 66.858%)			
Service robots will usually provide error-free service	4.42	1.521	0.841
Service robots will not fail me	3.90	1.514	0.814
Service robots will perform their intended task properly, as they were designed to do	5.29	1.287	0.797
Perceived robot functionality[a] ($\alpha = 0.804$, CR = 0.924, AVE = 72.067%)			
Service robots will have the physical features necessary to provide services	4.70	1.492	0.827
Service robots will have the functionalities necessary to provide services	5.03	1.322	0.868
Service robots will have the overall capabilities necessary to provide services	4.83	1.422	0.852
Perceived usefulness of service robots in tourism[a] ($\alpha = 0.939$, CR = 0.978, AVE = 84.575%)			
Service robots will be useful to me during my trip	4.80	1.486	0.927
Service robots will increase the convenience of the travel	4.73	1.532	0.906
It will be worth using service robots in a tourism/hospitality setting	4.69	1.568	0.915
Overall, I think service robots will be useful for my travel	4.77	1.582	0.930
Perceived advantages of robots compared to human employees[a] ($\alpha = 0.823$, CR = 0.906, AVE = 58.787%)			
Service robots will provide more accurate information than human employees	4.72	1.535	0.757
Service robots will make fewer mistakes than human employees	4.79	1.453	0.780
Service robots will be able to provide information in more languages than human employees	6.02	1.180	0.723
Service robots will be faster than human employees	5.16	1.410	0.774
Service robots will deal with calculations better than human employees	5.71	1.304	0.797
Perceived disadvantages of robots compared to human employees[b] ($\alpha = 0.732$, CR = 0.868, AVE = 55.628%)			
Service robots will not be able to do special requests	3.15	1.539	0.794
Service robots will only be able to deal with/operate in standard situations	2.80	1.357	0.735
Service robots will not understand if a guest is satisfied with service	3.27	1.610	0.735
Service robots will misunderstand a question/order	3.43	1.409	0.717
Robotic service experience expectations[a] ($\alpha = 0.891$, CR = 0.945, AVE = 65.601%)			
I will feel uneasy when being served by service robots (r)	4.17	1.761	0.693

Table 4 (continued)

Variable	Mean	Standard deviation	Item loadings
I will feel comfortable talking to/interacting with a service robot	4.49	1.668	0.812
Being served by robots will be a memorable experience	5.01	1.553	0.771
Being served by robots will be a fun experience	4.98	1.587	0.862
Being served by robots will be an exciting experience	4.85	1.631	0.866
Overall, I will have positive experiences when being served by robots	4.67	1.430	0.843
Perceived emotional skills of robots[a] ($\alpha = 0.798$, CR = 0.945, AVE = 83.195%)			
Service robots will be friendlier than human employees	3.70	1.700	0.912
Service robots will be more polite than human employees	4.28	1.658	0.912

Extraction method: Principal Component Analysis; Rotation method: Varimax with Kaiser Normalization

Coding: [a]1-stringly disagree, 7-strongly agree, [b]1-strongly agree, 7-strongly disagree, (r)—reverse coding

Sources of items: perceived robot reliability and Perceived robot functionality—adapted and expanded from Tussyadiah et al. (2017), Perceived usefulness of service robots in tourism—adapted and expanded from Venkatesh and Davis (2000), Perceived advantages of robots compared to human employees, Perceived disadvantages of robots compared to human employees, Robotic service experience expectations and Perceived emotional skills of robots—adapted and expanded from Ivanov et al. (2018a, b)

***Significant at $p < 0.001$

Table 5 Discriminant validity matrix

	Humans-robots ratio	Reliability	Functionality	Usefulness	Advantages	Disadvantages	Experience expecta-tions	Emotional skills of robots
Humans-robots ratio preferences	**0.8152**							
Perceived robot reliability	– 0.401***	**0.8177**						
Perceived robot functionality	– 0.410***	0.679***	**0.8489**					
Perceived usefulness of service robots in tourism	– 0.561***	0.594***	0.632***	**0.9196**				
Perceived robot advantages	– 0.408***	0.708***	0.668***	0.589***	**0.7667**			
Perceived robot disadvantages (r)	– 0.356***	0.288***	0.309***	0.343***	0.191***	**0.7458**		
Robotic service experience expectations	– 0.558***	0.580***	0.597***	0.806***	0.570***	0.367***	**0.8099**	
Emotional skills of robots	– 0.400***	0.513***	0.525***	0.522***	0.522***	0.255***	0.549***	**0.9121**

Bold indicates the diagonal cells indicate the square root of AVE. Bivariate Pearson correlations in the cells below the diagonal

Levels of significance

***$p < 0.001$, 3 (r)—reverse coding

Table 6 Regression analysis results

Dependent variable: Humans-robots ratio preferences		Hypothesis number	Model 1		Model 2		Model 3		Model 4		Model 5	
Independent variables			Unstandardized Coefficients	t	Unstandardized Coefficients	t	Unstandardized Coefficients	t	Unstandardized Coefficients	t	Unstandardized Coefficients	t
Groups of variables	Variables		B		B		B		B		B	
	Constant		− 0.003	− 0.138	− 0.002	− 0.101	− 0.003	− 0.156	0.399	4.054***	0.250	1.658
Robot characteristics	Reliability	H1	− 0.164	− 5.159***	− 0.064	− 1.877	0.010	0.315	0.009	0.293	0.002	0.061
	Functionality	H2	− 0.184	− 5.726***	− 0.092	− 2.794**	0.028	0.896	0.037	1.189	0.037	1.174
	Emotional skills	H3	− 0.219	− 7.967***	− 0.170	− 6.307***	− 0.075	− 2.871**	− 0.074	− 2.871**	− 0.075	− 2.891**
Alternative servers	Robot advantages	H4			− 0.167	− 4.939***	− 0.079	− 2.463*	− 0.059	− 1.850	− 0.053	− 1.651
	Robot disadvantages (r)	H5			− 0.238	− 10.226***	− 0.164	− 7.387***	− 0.166	− 7.502***	− 0.159	− 7.207***
Robotic service experience	Experience expectations	H6					− 0.224	− 6.173***	− 0.193	− 5.251***	− 0.197	− 5.336***
	Usefulness	H7					− 0.267	− 7.314***	− 0.249	− 6.790***	− 0.247	− 6.738***
Attitudes towards robots	Attitude towards robots in general	H8							− 0.076	− 4.174***	− 0.068	− 3.679***

Table 6 (continued)

Dependent variable: Humans-robots ratio preferences		Hypothesis number	Model 1		Model 2		Model 3		Model 4		Model 5	
Independent variables			Unstandardized Coefficients	t	Unstandardized Coefficients	t	Unstandardized Coefficients	t	Unstandardized Coefficients	t	Unstandardized Coefficients	t
Groups of variables	Variables		B		B		B		B		B	
Tourist profile	Gender	H9.1									− 0.088	− 2.106*
	Age	H9.2									0.000	0.230
	Household size	H9.3									0.040	2.883**
	Education	H9.4									0.030	1.692
	Economic wellbeing	H9.5									− 0.032	− 1.882
	Travel frequency	H9.6									− 0.006	− 0.753

Table 6 (continued)

Dependent variable: Humans-robots ratio preferences		Hypothesis number	Model 1		Model 2		Model 3		Model 4		Model 5	
Independent variables			Unstandardized Coefficients	t	Unstandardized Coefficients	t	Unstandardized Coefficients	t	Unstandardized Coefficients	t	Unstandardized Coefficients	t
Groups of variables	Variables		B		B		B		B		B	
Model summary	R		0.477		0.534		0.618		0.624		0.630	
	R^2		0.228		0.285		0.382		0.389		0.397	
	Adjusted R^2		0.226		0.282		0.379		0.386		0.391	
	F– Statistic		148.969***		120.315***		133.332***		120.113***		70.542***	
	Standard error of the estimate		0.8804		0.8480		0.7887		0.7845		0.7812	
	ΔR^2		0.228		0.057		0.097		0.007		0.007	
	ΔF		148.969***		59.937***		118.946***		17.426***		3.107**	

Coding: Humans-robots ratio: 1—I prefer to be served only by robots, 4—I prefer to be served by approximately equal number of human employees and robots, 7—I prefer to be served only by human employees; *Gender*: 0 – Female, 1—Male; (r) – reverse coding; 2. *** Significant at $p < 0.001$, ** Significant at $p < 0.01$, * Significant at $p < 0.05$

models because all VIF values were smaller than five. The regression results indicate that the perceived emotional skills of service robots are positively related to tourists' preferences towards the share of robots in the service delivery systems of tourism and hospitality companies (H3). Note that the negative sign of the regression coefficient of emotional skills in all five models denotes that higher perceived emotional skills of robots are associated with a lower value of the humans-robots ratio. Considering the coding of the dependent variable (1—I prefer to be served only by robots, 7—I prefer to be served only by human employees), the negative sign of the regression coefficient shows a positive relationship between the perceived emotional skills of robots and the preferred share of robots in the service delivery system of tourism/hospitality companies.

Similarly, the robotic service experience expectations (H6), the perceived robot usefulness in the tourism/hospitality context (H7), and attitudes towards robots (H8) are positively related to tourists' preferences towards the share of robots but perceived robot disadvantages (H5) are negatively related to the humans-robots ratio preferences. The regression coefficients of robot advantages to human employees (H4) are statistically significant only in Models 2 and 3. Perceived service robot reliability (H1) is positively associated with the dependent variable only in Model 1, while perceived service robot functionality (H1) is positively associated with it only in Models 1 and 2, and this association becomes statistically insignificant when other explanatory variables are included in the regression models. Gender (H9.1) and household size (H9.3) are the only tourist profile variables that have statistically significant regression coefficients (Model 5). Specifically, females and those with larger households preferred a higher share of humans in the service delivery systems of tourism and hospitality companies compared to males and respondents with smaller households.

Additionally, the regression analysis shows that age (H9.2), education (H9.4), economic wellbeing (H9.5) and travel frequency (H9.6) are not associated with the humans-robots ratio preferences. Thus, regression analysis results support hypotheses H3, H5, H6, H7, H8, H9.1 and H9.3 and do not provide support for H1, H2, H4, H9.2, H9.4, H9.5 and H9.6. These results mean that people accept a high share of robots in the service delivery if they perceive robots as having high emotional skills and as useful in the tourism/hospitality context, expect that robots will be beneficial to their travel experience, generally have positive attitudes toward robots, consider that robots have fewer disadvantages compared to human servers, have smaller households and identify with the male gender (see Table 7).

5 Conclusion

5.1 Theoretical implications

The paper has several important theoretical implications. Firstly, the identified clusters all preferred to have human labour in specific hospitality/tourism contexts. This suggests that respondents still perceive the hospitality/tourism service environment as something that ideally should be dominated by human interactions, even if robots

Table 7 Hypotheses outcome

Hypothesis	Outcome	Comment
H1: Perceived service robot reliability is positively related to tourists' preferences towards the share of robots in the service delivery systems of tourism and hospitality companies	Not supported	Table 6: The regression coefficient is statistically significant only in Model 1
H2: Perceived service robot functionality is positively related to tourists' preferences towards the share of robots in the service delivery systems of tourism and hospitality companies	Not supported	Table 6: The regression coefficients are statistically significant only in Models 1 and 2
H3: Perceived emotional skills of service robots are positively related to tourists' preferences towards the share of robots in the service delivery systems of tourism and hospitality companies	Supported	Table 6: The regression coefficients are statistically significant in all five models (Models 1–5)
H4: Perceived service robot advantages compared to human employees are positively related to tourists' preferences towards the share of robots in the service delivery systems of tourism and hospitality companies	Not supported	Table 6: The regression coefficients are statistically significant only in Models 2 and 3
H5: Perceived service robot disadvantages compared to human employees are negatively related to tourists' preferences towards the share of robots in the service delivery systems of tourism and hospitality companies	Supported	Table 6: The regression coefficients are statistically significant in all four models (Models 2–5)
H6: Tourists' robotic service experience expectations are positively related to their preferences towards the share of robots in the service delivery systems of tourism and hospitality companies	Supported	Table 6: The regression coefficients are statistically significant in all three models (Models 3–5)
H7: Perceived service robot usefulness in tourism/hospitality context is positively related to tourists' preferences towards the share of robots in the service delivery systems of tourism and hospitality companies	Supported	Table 6: The regression coefficients are statistically significant in all three models (Models 3–5)
H8: Tourists' attitude towards robots is positively related to their preferences towards the share of robots in the service delivery systems of tourism and hospitality companies	Supported	Table 2: F-test values are significant at $p < 0.001$ Table 6: The regression coefficients in Models 4 and 5 are statistically significant
H9.1: Gender shapes tourists' preferences towards the share of robots in the service delivery systems of tourism and hospitality companies	Supported	Table 2: all but one t-test values are significant at $p < 0.001$ Table 6: The regression coefficient in Model 5 is statistically significant
H9.2: Age shapes tourists' preferences towards the share of robots in the service delivery systems of tourism and hospitality companies	Not supported	Table 2: only one F-test value is statistically significant Table 6: The regression coefficient in Model 5 is not statistically significant

Table 7 (continued)

Hypothesis	Outcome	Comment
H9.3: Household size shapes tourists' preferences towards the share of robots in the service delivery systems of tourism and hospitality companies	Mixed results	Table 2: only three *F*-test values are statistically significant Table 6: The regression coefficient in Model 5 is statistically significant
H9.4: Education shapes tourists' preferences towards the share of robots in the service delivery systems of tourism and hospitality companies	Not supported	Table 2: only one F-test value is statistically significant Table 6: The regression coefficient in Model 5 is not statistically significant
H9.5: Economic wellbeing shapes tourists' preferences towards the share of robots in the service delivery systems of tourism and hospitality companies	Not supported	Table 2: 7 out of 17 F-test values are statistically significant at $p < 0.05$ but only 3 of the post hoc pairwise comparisons were statistically significant Table 6: The regression coefficient in Model 5 is not statistically significant
H9.6: Travel frequency shapes tourists' preferences towards the share of robots in the service delivery systems of tourism and hospitality companies	Not supported	Table 2: none of the *F*-test value is statistically significant Table 6: The regression coefficient in Model 5 is not statistically significant
H10: Different clusters of tourists exist based on their preferences towards the share of robots in the service delivery systems of tourism and hospitality companies	Supported	Tables 1 and 2: Three distinct clusters are identified

are effective and can do many tasks. The mean scores in Table 2 should remind us that while respondents would accept more robots, they still preferred to be served by more humans than robots. Thus, respondents considered that robots should support service delivery, helping human employees rather than replacing them. This conclusion aligns with Seyitoğlu and Ivanov (2020)'s recommendation that a mixed service delivery system with human-robot collaboration is the most appropriate for the (post-) pandemic world.

Secondly, the findings also suggest that the emotional skills of robots play a critical role in supporting the use of robots in the labour mix. These findings fit well within the results of previous studies. The literature shows that customers expect robots to have emotional skills (Chuah and Yu 2021), and the emotional and social skills of service robots are considered significant drivers of customers' robot use intentions, attitudes and the actual use of robots in service contexts (Wirtz et al. 2018; Seyitoğlu et al. 2021; Stock-Homburg 2022). Hence, the higher the perceived emotional skills of service robots, the more likely the tourists are to use robots and accept a higher share of robots than human employees in the service delivery systems of tourism and hospitality companies—something confirmed by this study.

Thirdly, respondents' perceptions of the disadvantages of robotic labour had a far more robust relationship with the desired ratio of robots to humans than did their perception of advantages of robotic labour. What this means is that tourists consider the disadvantages of robots much more heavily with regard to determining the appropriate humans-robots mix in a service environment than is the case with advantages. This result is in line with Webster and Ivanov's (2021b) findings of the perceived appropriateness of autonomous vehicles in the tourism context.

Fourthly, previous research shows that robotic service experience expectations are positively related to the attitude towards robotic service in hotels (Ivanov et al. 2018a). In this aspect, tourists' expectations about service would increase their motivation towards intentions to use/buy a particular service (Kytö et al. 2019). Additionally, the usefulness of service robots is positively associated with the perceived value of service robots (de Kervenoael et al. 2020) and attitudes towards service robots in hotel services (Zhong et al. 2021), while the attitudes towards robots positively affect the use intentions (McLean et al. 2020; Meidute-Kavaliauskiene et al. 2021). In our context, the positive expectations about the robotic service, the perceived usefulness of service robots in tourism and the positive attitudes towards them motivated respondents to accept more robots in the service delivery systems of tourism and hospitality companies, thus indirectly indicating that they would support their wider implementation in tourism and hospitality.

Fifthly, the results illustrate that males prefer more robots in the service delivery systems of tourism and hospitality companies than females do, in line with previous studies (Ivanov et al. 2018a). The findings echo previous studies which found that males like things and females like people (Su et al. 2009), illustrating female scepticism towards the use of robots.

Finally, the findings show that the reliability and functionality of robots do not shape respondents' preferences towards the humans-robots mix in the service delivery systems of tourism and hospitality companies. Previous studies have shown that these robot characteristics are positively related to the perceived appropriateness of robots in passenger tourist transport (Webster and Ivanov 2021a, b), intentions to use robots (Tussyadiah et al. 2017; Cha 2020), and attitudes towards robots (Lin and Mattila 2021) but this study does not find a relationship between robots' reliability, functionality, and the humans-robots mix preferences of respondents. The reason might be that respondents see robots as collaborators to humans and prefer a mixed service delivery system (based on human-robot collaboration) to a pure robotic one. Hence, the human employees can compensate for a failure of the robot to perform a specific task (lack of reliability) or its inability to perform the task at all (lack of functionality). As a matter of fact, only between 2.5% (for restaurant service) and 6.9% (for room service) of respondents have indicated that they would prefer to be served only by robots (frequencies of responses not included on the tables but available from the authors).

5.2 Managerial and practical implications

The humans-robots mix in the service delivery system can be a complex and confusing issue for managers as various factors can influence customer preferences. In this vein, this section presents critical implications for tourism and hospitality industry managers and practitioners. Firstly, the findings of this research develop an empirical basis for tourists' preferences toward the humans-robots ratio in service delivery systems. The results demonstrate that participants of this study prefer more human servers in service delivery systems, especially for services such as restaurants and bars that require social interactions and emotional intelligence. However, customers prefer service robots, especially for repetitive services that require no or limited individual interactions. As the nature and characteristics of service environments and tasks are crucial to deciding the type of servers, managers must consider these issues in the design of the service delivery systems of tourism and hospitality companies. For example, while service robots can be used for the repetitive, dirty, and dull tasks in restaurants and bars, human employees would be better in these service environments for the direct services to the customers as they have social and emotional skills. Managers or owners should consider that human employees can be more suitable for the frontline hotel services, while robots could be more convenient for the back-of-house tasks. To sum up, the service environment and the task types are the crucial aspects that attention should be paid to by managers or owners in service delivery system designs.

Robot designers should consider the need for socially and emotionally intelligent service robots to be used in tourism and hospitality contexts. In this regard, the congruency of the service robots with the nature of the service context was also mentioned in the literature (Wirtz et al. 2018; Seyitoğlu et al. 2021) to be a significant issue, most notably for the tasks requiring communication, social and emotional skills. Moreover, Reis et al. (2020) imply that in their current forms, service robots may not be successful and efficient in replacing human employees for all the service contexts. That is because while robots are efficient in terms of moving items, cleaning, or performing repetitive physical tasks, they fall short when they need to communicate with or show emotions to customers and employees.

Finally, from the managerial perspective, tourism and hospitality firms should not consider only service robots or human employees for their service delivery systems; instead, they can adjust their humans-robots mix according to their customer profile and service characteristics to provide quality service and experience to their customers. Companies should not stick with one side (either robotic or human) because the combination of service robots and human employees simultaneously may allow tourism and hospitality firms to benefit from the strengths of both types of servers while compensating for their negative aspects. However, the target market segment is crucial for tourism and hospitality firms to design their service delivery systems and position in the market because each service delivery system appeals to a different market segment. Hence, knowing the tourist typologies and, their desires and expectations may help companies determine the humans-robots ratio in their service delivery systems. This is important as not every tourist would prefer service robots, while other tourists may be willing to pay more for a robotic service. The current literature also supports that for the tourism and hospitality industry, the knowledge of customer desires and expectations is vital in designing the service delivery system (Seyitoğlu 2021) because successful market positioning requires knowing the target market's expectations (Seyitoğlu and Ivanov 2020).

5.3 Limitations and future research directions

There are several limitations to this research that should be noted. First, the data were collected before the COVID-19 pandemic and subsequent political responses. So, it may be possible that the social, economic, and political environments have changed the attitudes of much of the population towards robots in tourism and hospitality, especially given the substantial removal of many people worldwide from the workforce in tourism and hospitality. However, it may be that the pandemic had no discernible impact on attitudes, so this research should be followed up by more recent data gathering to find out if there has been a substantial shift in attitudes.

Second, the data are more or less a global sample, although dominated by Bulgarian and US respondents. This may mean that some of the conclusions regarding the influences upon the variables may be country-specific rather than more generalised. It may well be that single-country studies may invalidate the multi-country data.

Third, it is possible that the humans-robots ratio was not fully conceptualised by many respondents. So that future studies may want to incorporate focus groups, scenarios, and simulations to allow respondents to explain their attitudes towards particular ratios better and will enable them to visualise more clearly what a more robot-intensive service environment would be like rather than a human-intensive service environment.

Fourth, future studies may shed more light on the types of tasks implemented in each of the analysed services (mostly physical tasks or cognitive/emotional tasks) and how they shape the respondents' preferences towards the humans-robots mix in the delivery process of the respective service.

Finally, the study did not pay attention to the psychological characteristics of respondents. Future research on the humans-robots mix preferences may utilise the

Technology Readiness Index (Parasuraman and Colby 2015) because customers' readiness could affect the acceptance of robots (Flavián et al. 2022).

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Declarations

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ARTICLES FOR FACULTY MEMBERS

AUTOMATED SOLAR AND ELECTRIC COMPOST BINS FOR THE TOURISM AND FOOD & BEVERAGE (HOTEL) INDUSTRIES

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Restaurants and robots: public preferences for robot food and beverage services

Stanislav Ivanov and Craig Webster

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Abstract

Purpose – *The hospitality industry in developed countries is under pressure due to labor shortages and it is likely more food and beverage operations will have to be automated in the future. This research investigates the public's perceptions of the use of robots in food and beverage operations to learn about how the public perceives automation in food and beverage.*

Design/methodology/approach – *Data were collected from a survey disseminated online in 12 languages, resulting in a sample of 1,579 respondents. The data were analyzed using factor analysis and OLS regressions.*

Findings – *The data also reveal that generally positive attitudes toward the use of robots in tourism and hospitality is a strong indicator of positive attitudes toward the use of robots in an F&B setting. The data also illustrate that the public's perception of appropriateness of the use of robots in F&B operations is positively related to robots' perceived reliability, functionality and advantages compared to human employees.*

Research limitations/implications – *The implications illustrate that the public seems to be generally accepting robots in food and beverage operations, even considering the public's understanding and acceptance of the limitations of such technologies.*

Practical implications – *The research suggests that a critical element in terms of incorporating automation into future food and beverage operations is encouraging consumers to have generally positive attitudes toward the use of robots in hospitality and tourism industries.*

Originality/value – *This survey is based upon the data gathered in multiple countries to learn about how individuals perceive the use of robots in food and beverage operations, illustrating the attitudes that will assist or hinder the automation of this service industry.*

Keywords *Robots, Attitudes toward robots, Acceptance of robotic technologies, Food, Beverage*

Paper type *Research paper*

Introduction

By 2020, only a century after the invention of the word "robot" (NPR, 2011), robots were responsible for much manufacturing (Ross *et al.*, 2018) and are increasingly involved in the service economy (Belanche *et al.*, 2020; Wirtz *et al.*, 2018). However, it has only been in recent years that robots have been increasingly used to provide services to hospitality guests (Ivanov and Webster, 2019a). The integration of automation technologies in tourism and hospitality is inevitable because of the advancement of technology (Mihelj *et al.*, 2019) as well as demographic factors (Webster, 2021) that limit the human labor available for service industries. Here we discuss the use of robots in hospitality and explain several hypotheses with regard to perceptions of the use of robots in food and beverage operations. Then, we explain the data collection on the topic, analyze the data with regard to the hypotheses and conclude explaining how the findings inform the incorporation of robots into food and beverage operations in the future.

Currently, there is a growing body of research on robots in tourism and hospitality (see, for example, Murphy *et al.*, 2017; Samala *et al.*, 2020; Tung and Au, 2018; Tuomi *et al.*, 2021), including in food and beverage operations (e.g. Berezina *et al.*, 2019; Cha, 2020; Lee *et al.*, 2018;

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Fusté-Forné, 2021; Hwang *et al.*, 2020; Omar Parvez and Cobanoglu, 2021; Seyitoğlu and Ivanov, 2020; Seyitoğlu *et al.*, 2021; Tuomi *et al.*, 2019; Zemke *et al.*, 2020; Zhu and Chang, 2020). Previous studies have shown that robots can be used to automate dirty, dull, repetitive and dangerous jobs as well as create entertaining and novel experiences for tourists. Specifically, investigating the use of robots for food and beverage is critical since such operations are labor-intensive, critical to the hospitality industry, and typically suffer from high turnover rates. The automation of the delivery of food and beverage services may alleviate many of the headaches that managers in hospitality face and such automation has already been used in the food industry to reduce labor costs (Ivanov and Webster, 2019b) and to provide better services (Kincaid and Baloglu, 2005). While there is a great deal of speculation about issues linked with the incorporation of automation technologies into food and beverage operations (see, for example, Berezina *et al.*, 2019), much of what is known about the perceptions of managers and customers based upon empirical data is from small samples of semi-structured interviews (Seyitoğlu *et al.*, 2021; Tuomi *et al.*, 2021), case studies (Seyitoğlu and Ivanov, 2020), or single-country surveys (Cha, 2020; Hwang *et al.*, 2020). Thus, understanding the current perceptions of the public with regard to automated hospitality services is necessary to understand how to better implement fuller automation into hospitality operations, something that will be needed in the not-so-distant future due to labor shortages and the increasing effectiveness of the technology.

This research note aims to identify the F&B tasks that customers consider as appropriate for robotization and the drivers of the perceived appropriateness of robot use in F&B operations. More specifically, the paper looks at the role of perceived robot reliability, functionality, advantages and disadvantages compared to human employees, and demographic characteristics of respondents and their impact on the perceived appropriateness of robot use in F&B operations. In this way, the research will help managers address the factors that hinder or facilitate the implementation of the robot in F&B operations. Functionality of a robot shows that it possesses the technical features (e.g. sensors, actuators), software and overall design that allow it to implement its intended tasks (e.g. cook food, make a cocktail, serve dish) while a robot's reliability shows how well it will perform these tasks. That is why, previous studies have found that the reliability and functionality of robots are significant components of the trust in robots (Tussyadiah *et al.*, 2020). Additionally, reliability and functionality are positively related to the intentions of tourists to use robots (Tussyadiah *et al.*, 2017). The perceived advantages and disadvantages of robots compared to humans show how respondents perceive the potential provider of a particular tourism/hospitality service (a robot or a human employee). The perceived advantages of robots compared to human employees are found to have a positive relationship with the attitudes toward the use of robots in a hotel; the perceived disadvantages of robots have a negative effect, but it is washed out when the general attitudes toward robots are included in the regression models (Ivanov *et al.*, 2018). Positive relationship between the perceived advantages and the perceived appropriateness of robot application in museums was recently reported by Webster and Ivanov (2022). The same study showed that the respondents who had more positive attitudes toward robots considered that robots are appropriate for implementation in museum context. Attitudes are a significant driver of customer acceptance of service robot as well (Zhong *et al.*, 2021).

Therefore, the hypotheses of this research note are as follows:

H1. Perceived robot reliability is positively related to the appropriateness of robot use in F&B operations.

H2. Perceived robot functionality is positively related to the appropriateness of robot use in F&B operations.

H3. Perceived robot advantages compared to human employees are positively related to the appropriateness of robot use in F&B operations.

H4. Perceived robot disadvantages compared to human employees are negatively related to the appropriateness of robot use in F&B operations.

H5. The attitude toward service robots in travel, tourism and hospitality is positively related to the appropriateness of robot use in F&B operations.

Methodology

To investigate the public's perceptions of the use of robots in travel, tourism and hospitality, a global survey was run from March 2018 to October 2019. The survey was developed in English and subsequently translated into 11 other languages to make it accessible to as many people globally as possible. The survey questions were developed with the Technology Acceptance Model (Venkatesh and Davis, 2000) in mind while looking specifically into the question of how technology's incorporation into the tourism and hospitality ecosystem would be expected to be perceived by consumers of tourism and hospitality services. Questions pertaining to the advantages and disadvantages of robot labor were adapted and expanded from Ivanov *et al.* (2018).

To ensure that translations were accurate, native speakers translated the survey based on the original English language version. The survey was sponsored, allowing for researchers to offer incentives for participation in the survey, to ensure higher response rates. The incentive for participation was five gift cards that were given to those who completed the survey and wished to be considered for a drawing enabling each person who had indicated interest to win a 100$ gift card. The funds for the incentive were provided by a research firm that supported the research to learn about consumer perceptions of automation in the industry. Permission was given by a US university's IRB board, permitting the survey to be launched and it was disseminated via social media and emails globally. The authors' social media and email contacts were the primary means by which the survey link was disseminated, with colleagues encouraged to forward the link to others.

This paper's sample includes 1,579 respondents who answered the questions related to the application of robots in food and beverage operations and had answered all questions asked in the survey. Since it was disseminated online, it would be impossible to estimate how many people saw the link but refused to take the survey, although there was a significant number who took part in the survey and terminated the survey at some point. Those that did not answer the relevant questions for this analysis were removed from the sample for this particular analysis. Table 1 illustrates the major characteristics of the sample.

To learn about perceptions toward the use of robots in food and beverage operations, several questions were asked, with responses being recorded with a seven-point scale. Respondents to the survey were asked, "*Please indicate which activities do you personally consider as appropriate to be performed by service robots in travel, tourism, and hospitality*," with responses of different activities in the food and beverage operations of hospitality. Table 2 illustrates the questions asked and the mean responses to the questions, based upon the seven-point scale. The scale consisted of one extreme "1 = Extremely inappropriate" and the other extreme "7 = Extremely appropriate." Several questions were also asked with regard to the reliability and functionality of robots as well as questions with regard to the advantages and disadvantages of robots relative to human employees, using a seven-point Likert scale.

In regressions, demographic data were added in the hopes that they would give insight into the perceptions of the appropriateness of using robots in food and beverage operations. The gender, age and education levels of the respondents were used as independent variables. However, in addition, the respondents perceived economic well-being and reported that frequency of travel was also added to the regressions. The respondent's subjective perception of economic well-being was added instead of a measure for their income levels, as income levels are a sensitive issue tending to lead to a refusal to answer. Such monetary data are hard to compare against respondents from many different countries. In addition, travel frequency was added, as it was suspected that frequent travelers may have a different relationship with hospitality industries than those who travel less frequently.

Table 1 Sample's characteristics			
Characteristic		*Total*	*Share*
Gender	Female	847	53.6
	Male	732	46.4
Age	18–30	781	49.5
	31–40	381	24.1
	41–50	234	14.8
	51–60	120	7.6
	61+	63	4.0
Education	Secondary or lower	219	13.9
	Two year/Associate degree	105	6.6
	Bachelor	507	32.1
	Postgraduate (Master, Doctorate)	748	47.4
Economic well-being	Much less wealthy than average for the country	42	2.7
	Less wealthy than average for the country	103	6.5
	Slightly less wealthy than average for the country	168	10.6
	About the average for the country	521	33.0
	Slightly more wealthy than average for the country	449	28.4
	More wealthy than average for the country	235	14.9
	Much more wealthy than average for the country	61	3.9
Times stayed in hotels during the last 12 months	None	170	10.8
	1–3 times	733	46.4
	4–6 times	377	23.9
	7 times or more	296	18.7
	Missing	3	0.2
Country of residence	United States of America	387	24.5
	Bulgaria	318	20.1
	China	74	4.7
	Taiwan	62	3.9
	United Kingdom of Great Britain and Northern Ireland	58	3.7
	India	60	3.8
	Turkey	43	2.7
	Italy	45	2.8
	Russian Federation	36	2.3
	Portugal	34	2.2
	Malaysia	32	2.0
	United Arab Emirates	25	1.6
	Brazil	22	1.4
	Spain	21	1.3
	France	20	1.3
	Germany	20	1.3
	Other (83 countries)	320	20.3
	Missing	2	0.1
Total		*1,579*	*100.0*

Findings

Table 2 illustrates that respondents were most receptive to robots taking orders for room service ($m = 5.37$), followed by cleaning the table ($m = 5.19$), delivering food and drinks in room service ($m = 5.16$), and providing information about the menu ($m = 5.14$). The respondents were least receptive to robots cooking food ($m = 3.77$). These data show that respondents see some differences between the various tasks that they feel are appropriate for robots to do concerning food and beverage. The paired samples' t-test values showed that the differences between the mean responses to taking orders for room service, cooking food and the other tasks were statistically significant at $p < 0.001$. The data illustrate that the respondents generally seem to

Table 2 Exploratory factor analysis

Constructs and items	*Mean*	*Standard deviation*	*Item loadings*	*Cronbach's alpha*	*Composite reliability*	*Variance extracted*	*KMO*	*Bartlett*
Perceived appropriateness of robot use in F&B operations[a]				0.931	0.959	62.129	0.931	11092.065***
Taking orders for room service	5.37	1.666	0.768					
Delivering food and drinks in room service	5.16	1.819	0.821					
Guiding guests to tables in the restaurant	4.84	1.918	0.816					
Providing information about the menu	5.14	1.832	0.763					
Taking orders in the restaurant	4.97	1.858	0.822					
Cooking food	3.77	1.966	0.672					
Serving food in the restaurant	4.54	1.953	0.871					
Making drinks (coffee, tea,. cocktails) in the restaurant/bar	4.51	1.956	0.751					
Serving drinks in the restaurant/ bar	4.52	1.979	0.861					
Cleaning the table	5.19	1.769	0.714					
Perceived service robots reliability[b]				0.748	0.899	66.623	0.686	1100.577***
Service robots will usually provide error-free service	4.41	1.528	0.838					
Service robots will not fail me	3.91	1.515	0.814					
Service robots will perform their intended task properly, as they were designed to do	5.29	1.288	0.796					
Perceived service robots functionality[b]				0.800	0.922	71.660	0.705	1509.220***
Service robots will have the physical features necessary to provide services	4.69	1.493	0.823					
Service robots will have the functionalities necessary to provide services	5.02	1.327	0.867					
Service robots will have the overall capabilities necessary to provide services	4.83	1.423	0.849					
Perceived advantages of robots compared to human employees[b]				0.824	0.907	58.963	0.831	2628.398***
Service robots will provide more accurate information than human employees	4.71	1.534	0.757					
Service robots will make fewer mistakes than human employees	4.78	1.465	0.775					
Service robots will be able to provide information in more languages than human employees	6.01	1.191	0.729					
Service robots will be faster than human employees	5.15	1.411	0.773					
Service robots will deal with calculations better than human employees	5.70	1.310	0.803					
Perceived disadvantages of robots compared to human employees[c]				0.736	0.870	55.983	0.763	1268.392***
Service robots will not be able to do special requests (*r*)	3.16	1.546	0.795					

(*continued*)

Table 2 Continued

Constructs and items	*Mean*	*Standard deviation*	*Item loadings*	*Cronbach's alpha*	*Composite reliability*	*Variance extracted*	*KMO*	*Bartlett*
Service robots will only be able to deal with/operate in standard situations (*r*)	2.79	1.356	0.736					
Service robots will not understand if a guest is satisfied with service (*r*)	3.29	1.612	0.735					
Service robots will misunderstand a question/order (*r*)	3.44	1.415	0.724					

Note(s): 1. Extraction method: Principal Component Analysis; Rotation method: Varimax with Kaiser Normalization
2. Coding: [a]1-Extremely inappropriate, 7-Extremely appropriate; [b]1-Strongly disagree, 7-Strongly agree; [c]1-Strongly agree, 7-Strongly disagree; (*r*) – reverse coding
3. Sources for statements: *Perceived appropriateness* – developed by the authors; *Perceived advantages* and *Perceived disadvantages* – based on Ivanov *et al.* (2018); *Service robots reliability* and *Service robots functionality* – adapted from Tussyadiah *et al.* (2017)
4. ***Significant at $p < 0.001$

believe that cooking food is the task that is best left to humans while taking orders, cleaning tables, supplying information, and delivering food to guests could be delegated to robots.

Exploratory factor analysis was also employed and the results are shown in Table 2, illustrating that the data could be condensed into five meaningful factors. Table 3 presents the discriminant validity matrix. The results show that the constructs have high internal consistency and discriminant validity.

For a full analysis of the perceived appropriateness of robot application in the food and beverage industries, multiple OLS regressions were performed and the results are reported in Table 4. The first model used two independent variables – reliability and functionality of robots. The model seems to have relatively high levels of predictability, with an adjusted R-squared of 0.324, as Table 4 illustrates. Also, perceptions toward the reliability and functionality of robots are systematically and positively related to the perceived appropriateness of using robots in food and beverage operations, regardless of the control variables added.

The other regressions are also insightful, illustrating the additional power of the regressions given the added independent variables. The second model illustrates that the addition of two independent variables that indicate perceptions of the advantages and disadvantages of robots compared to human employees is also positively related to the dependent variable. The subsequent models demonstrate some interesting findings, showing that the addition of the variable to measure a general attitude toward robots seems to have two substantial impacts. First, the independent variable that indicates a generally positive attitude toward robots increases the adjusted R-squared value to 0.41 (Models 3 and 4). Another interesting finding is that the addition of the demographic data suggests that only the age of respondents is associated with the dependent variables (Model 4). Most of the demographic variables failed to show any relationship

Table 3 Discriminant validity matrix

	Appropriateness	*Reliability*	*Functionality*	*Advantages*	*Disadvantages*
Perceived appropriateness of robot use in F&B operations	*0.7882*				
Perceived service robots reliability	0.498***	*0.8162*			
Perceived service robots functionality	0.545***	0.680***	*0.8465*		
Perceived advantages of robots compared to human employees	0.488***	0.706***	0.671***	*0.7679*	
Perceived disadvantages of robots compared to human employees	0.296***	0.261***	0.285***	0.165***	*0.7482*

Note(s): 1. The diagonal cells indicate the square root of AVE. Bivariate Pearson correlations in the cells below the diagonal. 2. Levels of significance: $^{***}p < 0.001$

Table 4 Regression analysis

Dependent variable: Perceived appropriateness of robot use in F&B operations	*Model 1* *Unstandardized coefficients* B	*Standardized coefficients* *Beta*	t	*Model 2* *Unstandardized coefficients* B	*Standardized coefficients* *Beta*	t	*Model 3* *Unstandardized coefficients* B	*Standardized coefficients* *Beta*	t	*Model 4* *Unstandardized coefficients* B	*Standardized coefficients* *Beta*	t
Constant	−0.002 [0.021]		−0.094	−0.002 [0.020]		−0.107	−0.874 [0.075]		−11.632***	−0.668 [0.125]		−5.341***
Reliability	0.232 [0.028]	0.232	8.200***	0.132 [0.031]	0.132	4.185***	0.079 [0.030]	0.079	2.585**	0.092 [0.031]	0.092	3.008**
Functionality	0.387 [0.028]	0.386	13.654***	0.296 [0.030]	0.296	9.827***	0.199 [0.030]	0.199	6.632***	0.185 [0.030]	0.185	6.141***
Advantages				0.172 [0.031]	0.171	5.542***	0.137 [0.030]	0.136	4.576***	0.135 [0.030]	0.134	4.536***
Disadvantages (*r*)				0.153 [0.021]	0.153	7.155***	0.121 [0.021]	0.121	5.836***	0.125 [0.021]	0.125	6.029***
Attitude toward service robots in travel, tourism and hospitality							0.179 [0.015]	0.294	12.011***	0.177 [0.015]	0.291	11.894***
Gender										0.008 [0.040]	0.004	0.191
Age										−0.007 [0.002]	−0.085	−3.825***
Education										0.018 [0.017]	0.023	1.065
Economic well-being										−0.013 [0.016]	−0.017	−0.785
Travel frequency										0.000 [0.008]	0.001	0.047
Model summary												
R	0.570			0.596			0.641			0.646		
R^2	0.325			0.356			0.410			0.417		
Adjusted R^2	0.324			0.354			0.408			0.413		
F-statistic	375.808***			215.485***			217.062***			111.247***		
Standard error of the estimate	0.8211			0.8025			0.7681			0.7649		
ΔR^2	0.325			0.031			0.055			0.007		
ΔF	375.808***			61.397***			128.386***			3.194**		

Note(s): 1. Standard errors in square brackets; 2. Coding: *Gender*: 0 – Female. 1 – Male; *Economic well-being*: 1 – Much lower than the average for the country, 7 – Much higher than the average for the country; (*r*) – reverse coding. 3. ***Significant at $p < 0.001$. **Significant at $p < 0.01$. *Significant at $p < 0.05$

with the dependent variable, apart from the age of respondents, showing that the younger respondents were more accepting of the use of robots in food and beverage operations.

In general, the regressions illustrate that the perceived functionality and reliability of robots are positively associated with the perceived appropriateness of the use of robots for food and beverage operations, providing support to hypotheses H1 and H2. Furthermore, the findings show that the perceived advantages of robots compared to employees are strongly and positively related to the perceived appropriateness of their application in the F&B context in all three models with that variable, while the perceived disadvantages are negatively related (the variable was reverse coded); thus supporting H3 and H4. Moreover, the attitude toward the use of robots in travel, tourism and hospitality is positively related to the perceived appropriateness of robot use in F&B, hence supporting H5. Therefore, the respondents accept the use of robots in F&B operations when they trust the reliability and functionality of the robots, their advantages over human employees, and when they have generally positive attitudes toward robots in tourism, while the perceived disadvantages of robots decrease respondents' acceptance of service robots in F&B.

Discussion and conclusion

The findings illustrate a great deal in regard to the perceptions of the use of robots in food and beverage operations. The results show that one of the hardest things to sell to the public will be that cooking will be done by robots. While previous research has researched scenarios in which robots were involved in food production and delivery (Seo and Jee, 2021), any concerns about specific tasks done by robots in the scenarios were not explored. Thus, the findings in this current research illustrate a hesitancy of the public to accept robots doing the specific task of cooking, since the methodology allowed for an assessment of the consumers' acceptance of using technology for specific tasks in a food and beverage ecosystem. This also stands in contrast with previous research that was based upon the viewpoints of scholars and robot manufacturers, as Berezina *et al.*'s (2019) exploration of the topic. It may be noted that there may be a commonly held belief among the public that the cooking of food requires not just the human's ability to mechanically manipulate and create foods but some sort of spiritual/artistic element. Overcoming this may be easier than one would expect if the cooking of food is presented as something that is fun to watch and can result in a tasty result. Demystifying the cult of the celebrity chef will face an uphill battle, though, as it may be that the public has a love for their celebrity chefs, seeing them as entertainment (Caraher *et al.*, 2000; Demirkol and Cifci, 2020), so it may be that robotic chefs may also be used as entertainment. This feeds into a larger issue with regard to automation versus authenticity in service industries (Seyitoğlu, 2021), with different markets and different consumers demanding automation or authentic service provision by humans.

Consistent with previous studies, the general attitudes toward robots are associated with the particular use of robots in service industries (see, for example, Malchus *et al.*, 2013; Ivanov *et al.*, 2018). This suggests that to understand whether a person accepts the application of robots in a specific context (e.g. in F&B operations), it is necessary to learn about a person's general attitude toward robots.

Additionally, the results show that gender does not play a role in influencing attitudes toward the use of robots in food and beverage operations. While much of the research (see, for example, Hudson *et al.*, 2017; Katz and Halpern, 2014; Pochwatko *et al.*, 2015) suggests that gender conditions attitudes toward robots, the findings in this research suggest that food and beverage operations may be quite different from many other applications of robots, without having substantial gender differences in perceptions. The data also suggest that there is a generational rift, illustrating that younger people are more accepting of robotic technologies in F&B operations. As such, this research fits neatly into the current research that looks into how different age groups perceive automation technologies (see, for example, Ezer *et al.*, 2009; Xu *et al.*, 2015), although some findings contend that age differences may not account for many of the differences in perception of robots (Backonja *et al.*, 2018). At any rate, it seems that the generational rift and perceptions of people of different ages warrant further investigation.

The main limitation of this research is that data collection was finalized just before the outbreak of the COVID-19 pandemic. It may be that the global pandemic has changed the public's perceptions of service robots in F&B operations. That is why future research needs to reassess the perceptions to check whether they have changed. Future research should explore a great deal more regarding the use of automation technologies in food and beverage since there is a predictable shortage of available labor in developed countries (Webster, 2021). Future research may focus on the willingness to pay for robot-delivered F&B services and the role of robots in creating memorable F&B experiences.

All-in-all, this research note illustrates that the further automation of food and beverage will occur upon the foundation of a population that seems to recognize the strengths and weaknesses of more automated operations. In terms of theory and methodology, the findings illustrate the value of breaking down operations into tasks that may be automated. Such a methodology illustrates that some specific tasks are deemed by the public as being more acceptable for robots to do. This suggests that future research should investigate tasks, rather than scenarios with robots involved, as the public seems to have a somewhat different view of the use of robots based upon tasks, rather than grand scenarios in which a person has to imagine being served food. What is especially interesting is that the findings highlight that the public seems to recognize the disadvantages of robots in such operations but it does not seem to undermine the general attitude toward the appropriateness of the use of such technology. In terms of actionable elements from the research, it seems that cultivating a population that has generally positive attitudes toward service robots will play a helpful role in terms of allowing for robots to become more integrated into food and beverage operations. However, there is also an indication that the public, in general, will be willing to accept greater automation of food and beverage services depending upon what the task is, meaning that some tasks will not just be easier to automate but will also have less consumer resistance to the use of robots for such tasks.

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ARTICLES FOR FACULTY MEMBERS

AUTOMATED SOLAR AND ELECTRIC COMPOST BINS FOR THE TOURISM AND FOOD & BEVERAGE (HOTEL) INDUSTRIES

Robotization and smart technologies in the hospitality industry / Baran, Z., Karaca, S., & Baran, H.

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Chapter 1
Robotization and Smart Technologies in the Hospitality Industry

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ABSTRACT

New-gen technologies have profoundly impacted all aspects of life and various economic sectors. The tourism industry, known for its inclination towards innovation, has been quick to embrace technological advancements. In response to the global pandemic, tourism businesses such as hotels, food services, and transportation have increasingly utilized robotic systems to ensure social distancing, hygiene, and sanitation measures. However, digitization presents significant challenges for the tourism industry, requiring companies to adapt their operations to stay competitive. Automation has emerged as a highly beneficial trend, simplifying tasks and introducing innovative processes to tourism business models. This enables companies to provide personalized services tailored to the preferences of "digital tourists." Overall, new-gen technologies are reshaping the tourism industry and driving it toward enhanced efficiency and customer satisfaction.

INTRODUCTION

The tourism industry is undergoing great transformation and unprecedented change. Digital processes and innovative solutions driven by new-generation technologies have led to the emergence of new players and models. The industry has gained a new dimension with smart technologies that offer unprecedented

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application opportunities (Neuhofer et al., 2015). Hotels are one of the core structures of the tourism industry and new technologies in this field also encourage the development and innovation of the hotel industry. One important way to differentiate in the hotel industry is by offering added value through technology (Smartvel, 2020).

According to the International Federation of Robotics, a service robot is a type of autonomous robot that performs useful tasks for humans through sensing and adapting to different situations without human intervention (Paral, 2022). Service robots are defined as social intermediaries that can replace human service providers in service trials (Van-Doorn et al., 2017). Bowen and Morosan (2018) defined service robots as "physically embodied, artificial intelligence (AI) agents that can perform actions that have effects on the physical world." According to Ivanov, Webster, and Berezina (2017), service robots are "programmable, intelligent devices with a certain degree of autonomy, mobility, and sensory capabilities designed to perform a specific task" that are useful to humans. The term "social robot" is used to describe service robots that have the ability to interact and communicate with humans and follow social norms (Chi et al., 2020). Service robots are expected to play an increasingly important role in the hospitality and tourism industries, improving the service experience and quality (Mende et al., 2019). The use of robots in tourism and hospitality enterprises has the potential to enhance guest experiences and make them more efficient and enjoyable (Ivanov et al., 2017).

Robotic applications are widely used in manufacturing, military forces, medicine, and home care services. So, these applications are becoming increasingly common in hospitality and tourism (Murphy et al., 2017). The use of robots in the hospitality and tourism industry is one of the most modern, innovative, and advanced ever. The use of service bots ranges from basic AI chatbots to assist with the service process to sophisticated assistant bots that enhance the guest experience and satisfaction. As the number of companies using service bots increases, it is important to understand their impact on both business and customer satisfaction (Belanche et al., 2020). While some of these robots perform basic and routine tasks in hotels and restaurants, such as robotic floor cleaners (Murphy et al., 2017), the potential for their use in the industry is vast and varied.

The topics of AI and robotic technologies are rapidly spreading and widely used around the world, and are being studied by various disciplines in the literature. The field of tourism is also gaining attention as one of the disciplines in which research has been conducted in recent years. In this context, robots play a significant role in the application areas of the tourism sector (Kılıçhan & Yılmaz, 2020). Especially in light of the great developments in the field of information and communication technology, as well as the use of AI techniques in many areas, including tourism, smart technology has gained significant importance in the tourism industry today.

The objective of this chapter of the book is to provide an understanding of the concept of smart hotels and the application of new technologies in this field. It aims to create a discussion platform about the use of new technologies in smart hotels. To achieve this goal, the concept of smart hotels and the new-generation technology components that make up this concept will be explained based on the literature. Finally, a futuristic outlook will be presented in the conclusion chapter using the theoretical information obtained.

BACKGROUND

The hotel industry is putting more emphasis on smart and digital technology solutions and systems, such as AI, that can provide innovative solutions to meet the needs of tourists. As a result, the use of smart technologies is becoming more widespread every day (Kim & Han, 2020). China is a leading country in this field, having followed guidelines to build smart hotels for its tourism market since 2013. Many Chinese tech companies have been contributing to the digital transformation of traditional hotel business models to provide a better and more personalized tourist experience (The Economist, 2021). For instance, Fliggy (Alibaba Group's online travel platform) launched FlyZoo Hotel in Hangzhou in 2019, which offers a wide range of AI services. The hotel is considered a smart hotel because it uses many smart installations offered by Alibaba Group, according to Liang Bo, the hotel's Vice President. Similarly, Andy Wang, CEO of FlyZoo Hotel, notes that smart technologies are transforming the industry, and FlyZoo Hotel bridges the gap between hospitality and technology, inspiring and empowering tourists (Law et al., 2022).

Innovation is one of the key components of success in a competitive industry. However, in order to foster and implement it, it is crucial to be aware of the competition, potential risks, and challenges. Moreover, it can be challenging to predict whether tourism policymakers will support or obstruct investment in the development of innovative programs. For instance, some innovative strategies may clash with the traditional views of institutions, which could require collaboration with various stakeholders. Another factor to consider is crises within the tourism sector itself, as opposed to economic crises affecting a country. In such situations, requests for change from the private sector are often seen by politicians as pressing issues that require special attention and effort. (Rodríguez-Antón & Alonso-Almeida, 2020). Improving the tourist experience is a primary objective of innovative practices. Understanding tourists' perspectives on the use of new technologies in the hospitality industry is crucial in determining how well smart technology services can meet their expectations. The COVID-19 pandemic has accelerated the adoption of new technologies in the industry that help maintain, reduce, or eliminate social distancing (Davari et al., 2022). However, it is important to understand tourists' views on the use of these technologies to ensure that the services provided meet their expectations.

Smart Hotels

Smart hotel studies are derived from the field of global intelligent building studies and rely on advanced computer technologies that are constantly evolving (Frank et al., 2007; Doukas et al., 2007; Buckman et al., 2014; Leung, 2021). Smart hotels are prominent in countries such as the USA, China, Korea, and Singapore (Koo et al., 2013; Xu, 2018). Novotel Ambassador Seoul Dongdaemun in Korea stands out as a notable example of a smart hotel. The hotel is powered by AI from Hotels & Residences in Korea, and it offers AI room service with GiGA Genie, making it a new AI service platform (Gupta et al., 2022). In Singapore, the use of smart hotel technologies is supported by guidelines such as the "Smart Hotel Tech Guide 2018" and the "Technical Guide of The Smart Hotel 2019" published by the Singapore Hoteliers Association. These guides emphasize the importance of using technology in the tourist experience and are used in the hotel industry to provide better experiences. In China, smart hotels are being developed as an extension of smart tourism. The most prominent examples of smart hotels include the Penguin Hotel QQ chain and the FlyZoo Hotel opened by Alibaba Group (Luo & Pan, 2021).

Smart hotels are part of the broader trend in the hospitality industry toward the use of advanced technologies to enhance the customer experience. The concept of a "smart" hotel room involves a microprocessor-operated station that monitors essential parameters for the room's functioning, such as temperature, guest movement, and sensors. These stations are often connected to a central computer, allowing for centralized control of multiple rooms, floors, or even the entire hotel. In addition to room technology, smart hotels also offer guests self-check-in/check-out, mobile key access, remote room control, voice assistants, and digital guest services (Petrevska, 2016). However, technology plays an important role, smart hotels aim to provide a sustainable management model while still prioritizing guests' satisfaction. Ultimately, the hospitality industry is centered around people, and smart hotels aim to enhance the guest experience while maximizing efficiency. A timechart of smart hotel development worldwide can be seen in Table 1.

Table 1. Development of smart hotels

Year	Country	Example	Technology
2006	USA	Cobono Mountain Resort Pennsylvania	RFID system introduced
2009	USA	City Center Hotel Las Vegas	Implemented smart systems to identify personal preferences and improve accommodation experience
2009	China	Dragon Hotel Hangzhou	RFID and connected smart technologies, hotel management system
2013	China	National Tourism Administration	Official guide of "smart hotel construction and service"(LB/T 020-2013). This document provides guidance for hotel investors and operators in China and sets the quality and standards required for hotel construction and services.
2016	China	Smart Hotel Alliance	Celebrating China's Smart Tourism Year and establishing
2017	China	Penguin Hotel QQ	Development smart rooms
2018	Korea	Novotel Ambassador Seoul Dongdaemun	AI room service with GiGA Genie
2018	Singapore	The Singapore Hoteliers Association	"Smart Hotel Tech Guide 2018"
2018	China	FlyZoo Hotel Alibaba Group	It is the first hotel in the world to use a full-face recognition system. This hotel allows guests to check-in/check-out and check-in to their rooms using facial recognition technology. In addition, the hotel uses AI technology to understand guests' needs and provide better service
2019	Singapore	The Singapore Hoteliers Association	"Technical Guide of The Smart Hotel 2019"

The table highlights the development of smart hotels in different countries and the use of various technologies to enhance the customer experience. In China, the Dragon Hotel Hangzhou was the first to adopt smart technologies such as RFID and connected smart technologies, as well as a hotel management system developed by IBM. In Korea, the Novotel Ambassador Seoul Dongdaemun was the first to adopt AI room service through GiGA Genie. In Singapore, the development of smart hotels is supported by the publication of guidelines such as "Smart Hotel Tech Guide 2018" and "Technical Guide of The Smart Hotel 2019" by the Singapore Hoteliers Association. In China, the Penguin Hotel QQ chain and FlyZoo Hotel are examples of the latest smart hotel developments.

Internet of Things (IoT)

IoT, which stands for the "Internet of Things," is a global system consisting of interconnected computer networks that use standard internet protocols (Nunberg, 2012). In recent years, the IoT has enabled the emergence of elements that facilitate life by enabling communication of network-connected physical objects at any time and any place (Kosmatos et al., 2011). The IoT can be thought of as a global network system that provides a unique identity to each object, enabling communication from human to human, human to object, and object to object (Aggarwal & Lal Das, 2012). IoT defines a world in which almost everything can be connected and communicates intelligently, like never before. The term "connected" is often considered in terms of electronic devices such as servers, computers, tablets, and smartphones, but in the system called the Internet of Things, sensors and actuators embedded in physical objects are connected to each other through wired and wireless networks, and usually use the same Internet IP to connect to the Internet. These networks distribute huge amounts of data that flow to computers for analysis. Objects become tools to understand and respond quickly to complexity when they can both perceive the environment and communicate. The revolutionary aspect of all this is that these physical information systems can be coded and networked on the internet by intelligent technologies (Butler, 2020). This situation is considered an important detail that proves the availability of the IoT system by smart hotel systems (Han et al., 2021).

RFID (Radio Frequency Identification)

RFID (Radio Frequency Identification) technology is a crucial part of the IoT system (Liya et al., 2022) and can be applied in various fields such as agriculture, transportation, medical, and tourism where wireless network technology is used. RFID is also utilized in monitoring systems to track changes in the environment or specific geographic areas. It has the capability to reduce the labor required for inventory creation and security management effectively (Kaur et al., 2011). The first implementation of RFID technology in the hospitality industry was introduced at the Cobono Mountain Resort in Pennsylvania, USA in 2006. This technology enables guests to access their rooms and resort services using their keys or cards. USA in 2009, City Center Las Vegas Hotel implemented a smart system to determine their customers' personal preferences. This system allows for automatic check-in/check-out operations, controls heating-cooling systems, and simple functions such as room light curtains and restaurant reservations. The system also records past visits and the preferences of guests to provide more personalized services in future visits. In conclusion, RFID technology provides a convenient and personalized experience for guests in the hospitality industry by controlling simple functions such as room light curtains and making restaurant reservations. Additionally, the technology records past visits and preferences to enhance future customer service (Ren, 2014).

AI (Artificial Intelligence)

AI is a system that is based on large data processing capacities, and algorithms (Bulchand-Gidumal, 2022). John McCarthy organized the Dartmouth Conference in 1956, which was the first event focused on AI, and defined the term AI as "the science and engineering of intelligent machines, where intelligent machines are defined as those that can perform tasks that typically require human intelligence such as perception, reasoning, learning, and language understanding" (McCarthy, 2007). According to another definition, AI is a branch of computer science or the ability of a machine to imitate human behavior by simulating human intelligence (Webster, 2021). AI today offers services such as image recognition voice-activated search, and chatbots in mobile devices (Boden, 2017). The use of AI technology continues to grow with the advancement of algorithms development, access to new technologies becoming more affordable, and the participation of major technology companies in the tourism industry. Advanced technologies are required to enable smart hotel functions. AI technology is considered an important factor in the innovation of smart hotel services due to its technical advantages (Wang et al., 2020). On the other hand, AI is described as machine technology that understands, learns, and perceives like humans in the hospitality industry. From a practical implementation perspective, it is a smart machine system that has the ability to store and use information in the service process. In this context, it is described as a system that produces alternative solutions to human intelligence to help with the efficient use of all resources and to solve problems (Winston, 1993).

This table provides a high-level overview of the development of AI, including the key events and characteristics of each era. The first wave of AI, often referred to as "birth," refers to the early development of AI and the creation of basic computer programs and systems that could perform simple tasks. This period, which took place in the 1950s and 1960s, saw the creation of early AI technologies such as expert systems and decision trees. The second wave of AI, "development," saw the expansion of AI research and the creation of more advanced AI technologies. This period, which took place in the 1980s and 1990s, saw the creation of new AI technologies such as neural networks and genetic algorithms. The third wave of AI in the 1990s and present, "innovation," is often referred to as the current stage of AI development. This stage is characterized by the integration of AI technologies into a wide range of industries and applications, including healthcare, finance, transportation, and retail. Additionally, this wave is marked by the development of more advanced AI technologies, such as deep learning and reinforcement learning, or practical applications such as Siri, and Alexa, which are now being used to solve more complex problems. On the other hand, Perceptual Intelligence has emerged as a technology that aims to imitate human perception and intelligence in the field of AI. This technology grants machines the capability to perceive and understand sensory input through sound and vision. Perceptual intelligence refers to a type of AI that is designed to understand, interpret, and respond to sensory information from the physical world. It refers to the ability of AI systems to perceive, analyze, and understand data from a variety of sources, including images, videos, audio, and other forms of sensory data (Pentland, 2000). Perceptual intelligence is a key component of many AI applications, such as computer vision and speech recognition. For example, computer vision systems use perceptual intelligence to process and analyze images and videos, while speech recognition systems use perceptual intelligence to transcribe and interpret spoken language. In addition to its applications in specific domains, perceptual intelligence is also a critical component of more general AI systems that require a deep understanding of the sensory world. These systems often rely on machine learning algorithms, such as deep learning and reinforcement learning, to develop their perceptual intelligence over time (Pentland, 2001). However, the capability to comprehend, a crucial aspect of human intelligence, remains to be fully replicated. In a report released in 2020, it was noted that AI technologies in the field of Perceptual Intelligence have reached and even exceeded human standards, but the field of Cognitive Intelligence is still in its developmental stage (Li, 2021)s. In conclusion, the greatest advancements have been made in the field of Perceptual Intelligence, which is now considered the 3rd wave of AI technology development, and it is widely utilized across various industries.

AI Types Based on Approach

AI is usually divided into three approaches;

- Knowledge-based AI: At this level, the machine operates based on predefined knowledge. For example, a chatbot utilized provides pre-determined responses in customer service applications (Rodgers, 2020).
- Learning-based AI: At this level, the machine has learning capabilities in addition to its pre-defined knowledge. For example, a chatbot can learn from customer interactions, as well as from pre-programmed information (Nirala et al., 2022).
- Neural network-based AI: At this level, the machine acquires and performs through neural network algorithms. For example, designed to comprehend and respond to customer inquiries through the use of neural networks in customer service applications (Chen et al., 2022).

AI Types Based on Functionality

AI is usually divided into four basic functionalities. In Table 2, the types of AI based on their capacities are presented as a template:

Table 2. AI classification based on approaches

Category	Ability	Characteristics	Example
Mechanical	Automatically execute repetitive and routine tasks (Sternberg, 1997)	Mechanical AI is developed with restricted learning and application capabilities to ensure consistency. Not particularly smart.	Factory robots.
Analytical	Learning problems from the process in order to provide a solution using process information. (Sternberg, 1984-2005)	Analytical AI is considered "weak AI" as these AI applications can exhibit intelligent behavior, but cannot replicate human intuition.	Executing tasks by using the model created from learning the necessary knowledge and abilities
Intuitive	Thinking and adapting efficiently to new circumstances (Sternberg, 1984, 1999, 2005).	Intuitive AI is considered "strong AI" as it is designed to be more adaptable and function more like a human. Understanding is the most critical aspect.	Capable of producing original solutions to problems by utilizing prior knowledge and algorithms
Empathetic	Emotional (Empathetic) Intelligence (Goleman, 1996)	Empathic AI refers to a machine that can perceive, or at least simulate having emotions.	Robots that interact with humans using emotional intelligence features. Replica is utilized to comprehend human emotional states and provide appropriate responses. The Sophia Hanson robot is able to recognize and comprehend human emotional states by utilizing emotional intelligence technologies during human interactions.

Source: SHA, 2019

- Mechanical AI: AI systems can be used to automatically perform routine and repetitive tasks. For example, robots used in production lines in a factory can automatically carry out repetitive movements. In addition, AI systems can also be used in routine processes such as data entry or data processing (Huang & Rust, 2021). For example, in a call center application, AI system can automatically classify call records or, in a bill processing application, AI system can automatically verify invoice information (Vanneschi et al., 2018). AI systems are well-suited for performing routine and repetitive tasks, as the processes involved in these tasks typically have a fixed and standardized structure. These systems learn and execute operations based on the established model for such tasks (Fischer et al., 2020). This enables AI systems to perform routine and repetitive tasks instead of humans, allowing humans to focus on more valuable tasks.
- Analytical AI: Operational knowledge encompasses the specific knowledge and skillset required to carry out a particular task, such as operating a machine on a production line. The acquisition of operational knowledge and skills is an essential component of the learning process for individuals tasked with performing these types of duties (Friedlander & Zoellner, 2020). AI systems try to decode computing information using the learning process. For example, AI system gains an understanding of the knowledge and skills required to perform a task, and it then performs operations based on the learned model. In this way, AI systems can perform tasks that require processing knowledge instead of humans, so allowing humans to focus on more valuable tasks (Harris & Davenport, 2005). During the learning process, AI system identifies and learns from mistakes. In this manner, AI system continually improves its performance in processing information. This process of acquiring knowledge and skills for task completion can be considered learning.
- Intuitive AI: AI systems adapt effectively to new situations with the ability to think creatively. This process enables AI systems to generate unique solutions and find suitable solutions for new situations by using previously learned information and algorithms. According to Sternberg (1984), the ability to think creatively enables humans and AI systems to solve problems presented to them in ways that have not been solved before. In this process, AI system can produce unique solutions by using previously learned information and using the information learned during the learning process. Sternberg's (1999, 2005) creative thinking enables individuals and AI systems to solve problems in innovative ways, which were not used previously. In this process, AI system uses previously learned information and algorithms, can generate unique solutions, and find suitable solutions for new scenarios.
- Empathic AI: Emotional intelligence enables individuals and AI systems to identify and comprehend the emotions of others. This ability enables AI systems to perform in effective interactions with humans. It enables humans and AI systems to recognize and understand other people's emotions. In this process, AI system can give emotionally appropriate responses by recognizing and understanding other people's emotional states. AI system can influence other people's emotions and improve people's emotional state during these interactions. Empathic AI technologies and algorithms, as described by Goleman (1996), allow AI system to recognize and understand the emotions of others. AI is used in many various applications for example, smart systems can adjust room temperature, lighting, curtains or blinds automatically, leveraging AI technologies in hotels. Moreover, AI technologies can automate hotel booking processes and streamline check-in and check-out procedures.

AI Specific Systems Applies

According to AI Development Report (2011-2020), eight AI systems specifically applied in hospitality are highlighted:

- Machine Learning: It enables systems to learn and use from the data information.
- Robotics: It involves programming robots with AI technologies to automate tasks and improve efficiency. It is widely used for tasks such as transporting heavy materials in hospitality.
- Information Access: It enables systems to retrieve and analyze data to generate insights.
- NLP (Natural Language Processing): It allows systems to process, understand, and generate human language.
- Voice Recognition: It allows systems to recognize voice signals and convert them to text.
- Face Recognition: It allows systems to recognize face or image.
- Emotional Intelligence: It enables systems to detect and interpret human emotions.
- Social Intelligence: It enables systems to understand and engage social interactions.

In this context, AI technologies commonly used in hotels are shown in Table 3 presents a template of the commonly used AI technologies in hotels.

Table 3. Support Technologies and Specific Applications of AI

Technology	Explanation	Example
Robotics	Today's robots have the capability to move independently, execute repetitive and simple tasks, and provide information based on the data obtained from their actions	ServiceBots
Self-service software *	Self-service software is technology designed with user-friendly features that allow users to control their own service experience, providing electronic support without the need for interaction with a service representative. This technology offers limitless possibilities, from how they are used to how they present themselves. * *This technology, which is not technically considered* AI, *is still marketed and used as AI product in the industry due to its advanced capabilities*	Check-in/Check-out
Speech recognition	This technology is capable of recognizing and understanding spoken language. It listens to the speaker's voice to interpret the meaning and intention behind what is being said. To accomplish this, the audio signal is processed using machine-readable technology.	The participant is intelligent
Image Recognition	Video analytics refers to the use of computer algorithms to analyze and extract useful information from video footage. The goal is to use this information to support decision making and improve operations. It's often used to identify objects and detect patterns or behaviors in real-time. For instance, face recognition technology is a type of video analytics that uses unique features in captured images or videos to match them with stored templates for identification or authentication purposes.	Face recognition
Person-computer interaction	Virtual reality is a technology that creates a simulated environment that allows users to experience images, sounds, and sensations as if they were in a real-life setting. For example, virtual reality can be used to preview a hotel room from a distance before making a booking decision. Virtual reality glasses provide a fully immersive experience by putting users inside a 3D digital environment. In this artificial world, users can move around, interact with virtual objects, and experience the environment as if they were physically present.	Virtual reality (VR)

Source: SHA, 2018

Virtual Reality and Augmented Reality

Augmented Reality (AR) is considered a cutting-edge technology that operates through sophisticated algorithms and recognition, offering advanced services and is considered one of the world's leading technological innovations (Ara et al., 2021). AR technology enhances the functionality of mobile applications in industries such as health, tourism, education, and e-commerce with features such as motion tracking.

Virtual Reality (VR), an evolution of AR, is a technology that enables users to immerse themselves in a computer-generated virtual environment. VR technologies utilize multimedia devices and computer simulations to create a realistic experience for the user (Cao, 2016). These technologies typically include a head-mounted display and can display a room-sized virtual environment (Gold & Mahrer, 2018). With the visual experience provided by VR glasses such as Oculus, it is believed that future activities will increasingly take place in virtual environments (Huerta et al., 2019).

The main objective of virtual reality (VR) and augmented reality (AR) is to immerse users in a parallel digital environment that feels as real as possible. This technology has proven especially beneficial in digital marketing, as it allows marketers to bring the tourist experience closer to the consumer before they physically travel. For instance, a high-definition video that shows a picturesque beach with turquoise waters and blowing wind can evoke emotions and increase demand. Although VR and AR are mainly used in digital marketing, they also have practical applications in promoting lesser-known and far-off destinations. With the current travel restrictions due to the pandemic, the interest in virtual travel has been growing steadily.

Nowadays, VR applications in the hospitality industry are used as a support to make tourist activities dynamic and interesting. For example, by using these technologies in guided tours to the ruins, tourists can be immersed in historical events. For hotel chains and accommodation businesses, a virtual visit is offered before booking a room. By launching the Best Western Virtual Experience program in 2018, it aimed to provide immersive experiences to its guests. This allowed guests to better understand the property, its amenities, services and surroundings before booking. Thus, they managed to improve customer trust and communication and reduced the number of complaints by 71%.

Today, VR is utilized in the hospitality industry to enhance the dynamic and engaging nature of tourist activities. For instance, by incorporating VR technology into guided tours of historical sites, tourists can be fully immersed in the experience. In the case of hotels and other accommodation businesses, virtual visits are offered to potential guests before they book a room. In 2018, Best Western introduced its Virtual Experience program to provide an immersive experience for its guests. This program aimed to improve guests' understanding of the hotel's property, amenities, services, and surroundings, thus increasing customer trust and communication and reducing complaints by 71% (Camilleri & Camilleri, 2018).

VR technology is used in two main areas in the travel industry:

- First, it is used to increase the capacity of customers in the process of handling rooms and in the process of collecting information, to enable them to have a better understanding of the rooms and make quick decisions. For example; 360° VR photos can be given, which is a web application that does not require equipment.
- The second is used to provide a personalized and innovative experience during hotel stays. For example; can be given smart landscapes that offer an interactive experience.

Virtual reality technology has two primary applications in the travel industry:

- Enhancing the customer experience in room booking and information gathering, by providing a better understanding of the rooms and enabling faster decision-making. For instance, 360° VR photos can be made available through a web application that doesn't require any special equipment.
- Providing a personalized and innovative experience during hotel stays, such as interactive smart environments.

Examples of VR applications in hospitality are presented in Table 4 as a template.

Table 4. VR application in hospitality

Situation	Example
Before stay	**Information and marketing regarding hotel rooms and facilities**
Length of stay	**To provide additional value to guests: - Offer the chance to fully immerse in local experiences from the comfort of their accommodations. - Utilize original content created specifically by the hotel, such as the history of the building and local stories, to enhance their stay.**

Source: SHA, 2018

The benefits and considerations for the adoption of VR applications are presented in Table 5 as a template.

Table 5. Benefits and considerations VR adoption for hospitality

Benefits	Challenges
Elevating the overall brand experience. Boosting customer confidence and promoting quicker sales. Decreasing the time and effort required by the sales team for extended property inspections. Facilitating more streamlined cross-selling opportunities for travelers. A cutting-edge technology not accessible to all clients. Costly for virtual reality glasses with immersive experiences. Developing compelling advertising campaigns aimed at consumers.	**A cutting-edge technology not accessible to all clients. Costly for virtual reality glasses with immersive experiences. Developing compelling advertising campaigns aimed at consumers. A cutting-edge technology not accessible to all clients. Costly for virtual reality glasses with immersive experiences. Developing compelling advertising campaigns aimed at consumers.**

Source: SHA, 2018

As the hotel industry falls under the service sector, its offerings are intangible. The benefits and factors to consider when adopting VR in the hotel industry, as stated by Casaló et al. (2015), include:

- Taking experiential marketing to a new level
- Encouraging buyers to make quick decisions by boosting their confidence
- Reducing the time and effort required by the sales team for extended property inspections
- Offering easier cross-selling opportunities to foreign guests

- Limited accessibility for customers without VR viewing equipment
- High cost for VR glasses offering top-notch experiences
- The need for compelling content to captivate the consumer

Nowadays the widespread use of online booking, hotels now have a valuable opportunity to provide customers with panoramic views of their accommodations and food and beverage offerings on their website and through online travel agencies (OTA) platforms. Typically, tourists do not visit the property before making a reservation, as rooms are often reserved before finalizing travel plans. While not all customers have specialized equipment, such as VR glasses, to view VR content, even a limited experience viewed without such equipment is still more engaging than static photos. Additionally, augmented reality (AR) can also be used for entertainment purposes. However, providing a high-quality and private AR experience can be quite expensive, as the necessary equipment is costly.

The restaurant and catering industry is not immune to the use of VR technology. VR can be leveraged to create immersive culinary experiences, although it has yet to achieve realistic simulations of taste and smell. Restaurants can use VR technology to enhance their dining experience, for example, by adding a virtual show during meal service at a Caribbean restaurant. Some restaurants, like Sublimotion in Ibiza, are already utilizing this technology to offer more than just signature cuisine, but rather provide a multi-sensory experience for diners. While VR technology may not be appealing to the majority of the population, it is viewed as a niche with potential for growth and improvement in the future.

AR technology is a critical tool in enhancing the travel experience for tourists, making it easier, more enjoyable, and more empowering. Real-time camera translation systems, access to ratings and reviews of destinations, and software like "Google Lens" for Android phones are among the technologies that are currently in development and have the potential to make travel easier. It is important for the marketing and travel industry to pay close attention to these technologies and make efforts to optimize and improve them.

INNOVATIVE TECHNOLOGIES INTEGRATION INTO SMART HOTELS

Innovative Hotel Management Systems have become increasingly important in the hospitality industry due to the challenges posed by economic globalization and the growing demands of consumers for high-quality services (He, 2019). Traditional hotel service models are often characterized by regionalization and high degrees of commercialization, but they may not be effective in a fiercely competitive market where individual hotels resort to improper means to attract tourists (He, 2019; Xue et al, 2021). In this context, enterprises need to adopt a business attitude of excellence, constantly improving their hardware measures such as enterprise personnel, system, and facilities (Xue et al, 2021). To ensure the normal operation of the enterprise and meet the requirements of the new era, the original system needs to be improved and adapted to the changing information environment. The drawbacks of the old system may gradually appear, necessitating innovative management departments to take preventive measures to reduce the negative impact on enterprise development. In addition, the training of staff members is also essential to continuously upgrade their professional capabilities and knowledge reserves, enhancing their work efficiency and soft power (Feng, 2015). The new innovation mode has proven to be effective in addressing the conservative thinking of the old business model, which often leads to a lack of communication among different working layers of the enterprise and reduces work efficiency. The innovative approach promotes internal staff learning and exchange, bringing significant benefits to the enterprise. With the implementation of Innovative Hotel Management Systems, hotels can meet the demands of modern life and consumer preferences, which lays a good foundation for the further improvement of enterprise interests (Xue et al, 2021). In summary, Innovative Hotel Management Systems have become crucial for enterprises to succeed in a fiercely competitive market. The integration of hardware and software measures, the adaptation to the changing information environment, and the continuous improvement of staff members' capabilities and knowledge reserves are critical to the effective implementation of these systems. The innovative approach fosters communication, learning, and exchange among different working layers, bringing substantial benefits to the enterprise.

The Smart World and Smart Cities plan (Abdoullaev, 2011) was created by China as part of the Five-Year Tourism Plan developed by IBM, designed to modernize and enhance the tourism industry (Tu & Liu, 2014; Zhang, 2016). For this purpose, various technological solutions such as data analytics, AI, IoT, and blockchain were offered to tourism organizations and businesses. The aim of the plan was to improve customer experiences and increase the effectiveness of the tourism sector by making the country an attractive tourist destination. In this context, the "Smart Hotel" model was first implemented in 2009 through a partnership between Dragon Hotel Hangzhou and IBM. Under the agreement between the two businesses, the hotel will be expanded and reconstructed, and the RFID and connected smart technologies developed for the Smart Hotel model will be used. This partnership will be carried out within the "Smart World" strategy proposed by IBM and the hotel industry and will be accepted as a guide for the construction and service of smart hotels. This development has increased the use of technology in the hotel industry and provided personalization of hotel services (Zhang et al., 2012).

Automated Services

Generally, service bots are preferred in areas such as customer service, production, and cleaning, as they attempt to enhance human-computer emotional interaction and understand customer emotions through technologies such as self-check-in/check-out, smart assistant, face recognition, voice recognition, and email recognition (Frank et al, 2017).

Self-Check-In/Check-Out

In a traditional hotel, check-in is performed at the reception, while a smart hotel offers two alternative check-in options: through a mobile phone app or kiosks. Face recognition technology is used for identity and visa verification, and automated service software records personal and payment information. Upon completion of all transactions, the guest can unlock their room using either the electronic key in the mobile app or a physical room card from the kiosk. Check-out can be performed in the same way. The specific applications of this technology are detailed in Table 6 based on a guide developed by the Singapore Hotel Association and presented as a template.

Technically, robotic systems connect three essential components for the hospitality industry:

Table 6. Specific application of self-check-in/check-out system

Situation	Example
Before stay	Personal data and accommodation preferences, passport information Credit card information Personalized marketing promotion
Length of stay	Identity and visa verification with optical character and biometric recognition Card activation with electronic access from a mobile phone or automatic distribution of room cards via kiosks (Automatic check-in machine) Remote room control (air conditioning, lights and TV) with the app Direct communication with the application for questions and requests (food-beverage, cleaning and reservation, etc.) Personalized marketing promotion Automatic check-out
Post stay	Lost property, invoice and contact information Personalized marketing promotion Reminder to share experience on social networks

Source: SHA, 2018

- PSB (Police Station Bureau) - a system that facilitates the transmission of guest information to the security office by scanning the guest's ID before their stay in hotels in China.
- PMS (Property Management System) - a system that automates hotel operations such as guest reservations, guest information, and online bookings.
- OTA (Online Travel Agency) - a platform that allows for the booking and payment of rooms through a mobile device.

The specific applications of this technology are outlined in Table 7, based on a guide developed by the Singapore Hotel Association.

Table 7. Benefits of adopting self-check-in system

Benefits	Adoption elements
Reducing the waiting time **Offering more comfort** **Best guest experience** **Personalized experiences** **Encourage consumption** **Ensuring security in the pandemic**	Mobile apps have limited download rates, especially for unconventional customers. There are risks that could lead to a breach of user privacy. User experience interfaces should be appropriately designed to encourage usage. Physical personnel can complement the use of automated service applications.

Source: SHA, 2018

Smart assistant

The smart assistant with voice recognition in hotel rooms is similar to a smart speaker in a home. The smart speaker is a voice-controlled device equipped with a personal assistant that offers a range of services such as information search, music playback, and conversational capabilities (Nakanishi et al., 2020). Table 8 presents examples of smart assistant applications in hotels as a template.

Table 8. Implementation of smart assistant

Topics	Categories
Reception requests	Comments and complaints Cleaning service Sign out Facility reservation Care Transport Wake-up call
Smart room	Temperature Lights Curtains Media devices
Emergency alerts **The weather forecast** **Guest guide** **Calls**	
Linking personal accounts	Calendar notes Shopping list

Source: Buhalis & Moldavska (2021)

Besides all the functions of a smart assistant at home, it also has special functions when used in a hotel room. Rooms are the centerpiece of hotel service and are where guests will spend the majority of their time during their stay. In this sense, the smart speaker enables guests to easily and comfortably contact reception to request services or control all the devices in their room, enhancing their overall experience. Upon returning to their room, they can lie on their beds, close the curtains, turn on the TV, and start to unwind, just as they would at home. Table 9 presents the smart assistant benefits and considerations in hotels as a template.

Table 9. Smart assistant benefits and considerations

Benefits	Adoption elements
The ability to free up human resources and reduce operating costs thanks to the perfect interconnection of workflows **Combining self-updating operating systems** **Better experience for guests**	Guest resistance; • Age/demographic characteristics • Importance of human service • Current habits Complex integrations Staff training requirement

Source: Buhalis & Moldavska (2021)

Its benefits for the hotel also make the hotel's operating system more efficient by freeing up staff with voice recognition technology and providing a personalized experience for guests to enhance their stay. However, incorporating smart assistants into the hotel management system can be a challenging process. The assistant needs to be compatible not only with the hotel's operating system but also with all the smart devices in the room, such as curtains, lights, audio, TV, etc. Additionally, staff must be trained to handle guest requests made through the assistant and to assist customers, especially elderly or technology-resistant guests, in using the assistant effectively.

Face Recognition

Face recognition is widely used in technologies that provide an intelligent experience at the hotel. For example, it plays an important role in features such as the previously mentioned service robots and self-check-in system. The functional aspects of the facial recognition application in the hotel, the benefits it provides and the need to be adopted are presented in Table 10 as a template.

Table 10. Face recognition application

Function	Example
Reception	Fast registration and room lock processes of the guests, Automatic detection of guest arrivals, fast forwarding of guest profiles to reception and personal selling suggestions. Reducing waiting time by directing more staff through video detection of crowds in the lobby
Arrangement	To determine the food and beverage rights of the guests
Security	Reducing the need for intense patrols for human resources and monitoring of CCTV images with a smart security video system. To follow and identify unauthorized or suspicious people. Tracking and managing people more effectively.
Sales & Marketing	To detect guest emotional states, expressions and profiles and increase additional sales opportunities. Tracking and analyzing guests' routes and identifying sales areas

Source: SHA, 2019

These applications can be basically divided into three categories:

- Identification: Facial recognition can be used for identity verification instead of manual checks of identity documents and personal information, such as reservation details.
- Demand Assessment: Facial recognition can be used to assess customer demand and reduce wait times, allowing for actions to be taken to enhance the customer experience. For example, at the FlyZoo Hotel, the system can pre-program elevators when customers leave their rooms and walk towards them, eliminating the need to wait.
- Emotional Perception: Facial recognition can be used to gain a better understanding of a customer's satisfaction and needs, though its technology at this stage is not advanced enough to accurately detect real emotions and satisfaction levels. However, this is a future direction of technology development.

The benefits and considerations of adopting facial recognition technology are presented in hospitality in Table 11 as a template.Formun ÜstüFormun Altı

Face recognition technology, similar to other AI technologies, increases efficiency by performing tasks more rapidly, lowering operational expenses, and improving the customer experience. Additionally, this technology offers a distinct security advantage compared to other AI technologies, as it can prevent fraud. However, it is important to ethical and transparency concerns that arise from the fact that many current AI algorithms are "black box" (Li, 2021), and the process by which data is collected and processed are not transparent. Face recognition technology could infringe on individuals' privacy security without proper adherence to privacy protection laws.

Table 11. Benefits and considerations of adopting face recognition technology

Benefits	Adoption elements
The ability to free up human resources and reduce operating Increasing operational efficiency by automating manual and labor-intensive work. Providing clearer information to better make planning decisions Improving tourist safety and experience. Reducing operating costs and increasing revenue generation opportunities. To reduce losses and theft and increase security.	The risks of user privacy violations; inform about applicable privacy regulations. High investment budget for hardware such as smart cameras and system components. System reliability, risk of system failure and idle time. It may require high-end hardware and high video storage capacity that improves video analysis and resolution.

Source: Buhalis & Moldavska, 2021

Robotization

Robot refers to autonomous machine systems that perform the task for which it is programmed (Decker, 2008). AI robots aim to create systems capable of human-like thinking and learning through technologies such as machine learning, classification, prediction, and NLP. Robots are the most typical application of AI and often use machine intelligence for routine and repetitive tasks (Frank et al, 2017). Table 12 presents the usage areas of robot technologies in hotels as a template.

Table 12. Application of robots in hotel services

Area	Example
Welcoming, greeting, and transporting customers.	*Cheetah Greetbot*: The Cheetah Greetbot is a robot developed by Xiaomi that is used to greet and serve guests in hotel rooms. It facilitates check-in/check-out procedures, room availability checks, and access to hotel services.
Delivering guest services and food orders to rooms	*Robot Run*: The Robot Run at Henn-na Hotel Nagasaki in Japan employs roboserve robots to fulfill guests' food orders and service needs.
Presenting treats to customers in the restaurant	*Siyanchaoren*: The Siyanchaoren restaurant robot used in China is capable of performing tasks such as food delivery and cooking through the use of sensors, cameras, and robotic arms.
Preparing food, ice cream and drinks	*Purple honor robot*: The Purple Honor robots used in China are capable of performing tasks such as preparing, cooking, and serving food.
Delivering and picking up luggage to rooms.	*Bellhop*: he Bellhop robot used at the Los Angeles San Gabriel Sheraton Hotel uses walking technology within the hotel and takes precautions to avoid obstacles and pedestrians. It delivers guests' luggage to their rooms, making check-in more efficient and comfortable.

Source: SHA, 2019

However, the implementation of robotic systems used is a crucial issue in hotels. Understanding the benefits such as providing uninterrupted customer support, providing fast and accurate answers, reducing the workload, increasing customer satisfaction as a concept, providing cost savings, and collecting and analyzing statistical data will make the use of this technology widespread. Table 13 presents the main benefits and important features of robots as a template in hospitality.

Table 13. Benefits and considerations for adopting service robots in hospitality

Benefits	Adoption Considerations
Using an innovative approach in hotel marketing strategies to increase brand awareness.	Renting robots instead of purchasing them can reduce investment costs
Optimizing business processes to increase efficiency by reducing repetitive manual tasks and freeing staff to focus on more valuable customer interactions and essential business services.	The existing building infrastructure can pose mobility challenges for the adoption of robots, such as uneven floors and narrow aisles.
Improving guest satisfaction through the reduction of wait times and an increase in the factor of innovation.	Systems such as Wi-Fi should be seamlessly integrated with the autonomous robots
Performing tasks with increased accuracy and consistency.	It is recommended that hotel staff receive training in resolving basic problems.
The use of robots for deliveries instead of in-room service by male staff may increase comfort levels for female guests at the hotel.	It is recommended to employ technical personnel as they can quickly repair or recover broken robots without having to wait for suppliers, reducing downtime.

Source: SHA, 2018

Robotic Technology in Hotel Kitchens

As robotic technology continues to advance, it is becoming more common for machines to replace human workers in various industries. These robots are capable of performing tasks such as creating chain learning algorithms and using 3D pointer trajectories to carry out production and service tasks. In order to accomplish these tasks, the robots are programmed with information about the objects and properties that they will be working with. This programming is typically done through the use of targeted training images. One area where robots have become particularly useful is in the food industry. Robots are equipped with autonomous systems that provide cognitive support, allowing them to perform complex tasks with ease. Overall, while the increasing use of robots in the workforce may have some drawbacks, it also presents many exciting opportunities for innovation and efficiency in various industries (Pfau et al., 2019). Examples of the application of robotic technologies in the F&B department in the hotel industry are as follows (Feller, 2021):

Robot in the kitchen: There are many innovations in robotics used in the food industry, including salad robots, automatic pizza robots, fast food machines, bread-making robots, and virtual dark food processors (Feller, 2021). Robot chefs are able to prepare noodles, hamburgers, coffee, sushi, grills, and drinks (Ivanov et al., 2017). One notable example can be found at the Henn-na Hotel in Japan, where a robot chef prepares "ekonomiyaki" pancakes. A visitor who witnessed the robot in action reported that it was able to efficiently mix the dough, cook the pancakes with the use of two spatulas, and even wrap the finished product with mayonnaise and dried green algae without dropping a single pancake (Grey, 2016)

Robot Waiter (Server)/Robot Busser: Keenon Robotics (2022), a leading company in intelligent robotics, has introduced a range of reliable and effective robots in the hospitality industry due to the ongoing shortage of employees and high labor costs caused by the pandemic. One of the applications provided by the company is the server robot, which is specifically designed to serve customers and transport used plates and glasses for a more efficient guest service experience. It is equipped with the latest AI technology, including GPS technology. The use of robots as waiters is becoming increasingly common in the hotel food and beverage industry. Restaurant operators have been known to turn to robotic waiters when staff is unable to keep up with orders or when the number of waiters is limited (Cheong et al., 2016). Automated waiters and robots can assist restaurant staff during busy times, but excessive use of robots can result in layoffs for some employees (Ivanov & Webster, 2020). The Henn-na Hotel in Japan is the first hotel in the world to use human-like robots to serve its guests (Alexis, 2017). Pizza Hut has also hired the humanoid robot Pepper to take customer orders through voice recognition and AI-based technologies. Pepper not only takes orders and delivers them to the kitchen, but also accepts payments (Ivanov et al., 2017).

Robot Host/Stewardess: As robots are being used to drive sales, the Tanuki Restaurant in Dubai employs a host robot to greet guests upon entering the restaurant (Prideaux, 2019). The robot host can communicate with guests, offer discount coupons, and encourage repeat visits (Ivanov & Webster, 2020). Robot hosts can be seen as an alternative to human hosts for tech-savvy restaurants or those targeting younger customers. Interacting with these robots could be a unique experience for tech-savvy customers, adding an element of fun to their dining experience (Berezina et al., 2019)

Delivery Robot/Robotic Butler: In 2014, the Starwood Group introduced two robotic butlers named ALO at the Aloft Hotel. These butler robots allowed hotel staff to deliver necessary items, such as toothbrushes, towels, and water, directly to guest rooms (Crook, 2014). Instead of receiving cash tips, ALO asks guests to provide feedback and rewards high votes with a dance performance (Trejos, 2014). At the Flyzoo Future Hotel, guest's check-in using passport scans at kiosks and access their rooms with face recognition technology. The hotel's robot butlers also provide in-room services, such as turning on lights and closing curtains (Saiidi, 2019).

Robot Bartender: The Robot Bartender can come in both robotic arm and human form (Tussyadiah et al., 2020). Typically, the robot bartender is equipped with the ability to interact with guests, take and serve beverage orders, and perform its functions at the hotel bar (Giuliani et al., 2013). For example, Swiss bartender "Barney," created by F&P Robotics AG, is a fully automated machine capable of ***preparing*** dozens of cocktails to exact specifications, self-sterilizing, and even cracking jokes while serving food and drinks to customers (Smith, 2021). The bartender typically consists of two robotic arms positioned beneath the bottles at the bar (Berezina et al., 2019)

3D robotic system: 3D printing technology has progressed quickly and has enabled digitization of the entire manufacturing ***process***. It has gained popularity in the food industry due to its digital model that facilitates automation. One of the most widespread applications of 3D printing is food modeling. With the advent of new printing techniques, 3D printing technology is not only used for various food shaping purposes but also for micro-level food shaping (Chunhua & Guangqing, 2020). The primary objective of using the 3D Robotic system in the kitchen is to offer customizable products, optimize food parameters, and ensure precise preparation through 3D printing. Human limitations in the cooking process prevent the food from being prepared under the optimal taste and texture conditions. The implementation of the 3D Robotic system in the food industry addresses all crucial aspects such as proper data input, accurate parameter determination, process control, cooking degree and timing. To this end, Moley Robotics provides robotic tools for use in the kitchen. Established in 2015 with the goal of developing innovative food robot systems and a global taste and unlimited food variety, Moley Robotics stands out with its cutting-edge technology and unique designs in the kitchen. Two of the 3D robotic tools it offers are (Moley, 2015);

- Shadow *Robot* Hand; it all started with the realization that effectors with a three-fingered grip were stabilized at the level. Later, with the advancement of research towards creating a fully functional hand, the design of the robotic hand adopted the biological properties of human muscles. In this direction, the Shadow robot hand can mimic the function of muscles and can execute many movements in a timely manner (Tuffield & Elias, 2003). Replicating the wrist, which is the most complex structure of the human body, Shadow comprises 20 motors, 24 joints, and 26 microcontroller mechanisms. Shadow is considered one of the closest robotics kitchen tools to human hand sensitivity in countries such as the USA, China, and Japan (Barakazi, 2022).

- Moley Robotic Kitchen; It is a home kitchen-based robotic system designed to assist humans in meal preparation. This system comprises sensors, actuators, and other robotic components and is controlled by software that predicts the user's next action and provides personalized assistance. All these components are interconnected over the network and compare historical data in the database with the current sensor data, thus monitoring the cooking process and significantly simplifying preparation, especially with the use of 3D Robotics systems (Mizrahi & Zoran, 2023)

CONCLUSION

Digitalization and advancements in new-generation technology have had a significant impact on the tourism industry. In terms of tourism demand, it has made it necessary to adopt new technologies that allow for the provision of personalized and interactive services for tech-savvy tourists. Furthermore, success in an increasingly competitive environment is achievable only through the use of smart technologies, by adopting innovative methods and increasing competitiveness. AI, robotics, and new-generation virtual reality technologies have started to be integrated into tourism, leading to the emergence of "smart tourism" and "smart hotels." In the hospitality industry, which is a crucial component of the tourism enterprise, the use of robots can provide a competitive advantage for companies in the future as consumer markets and technology continue to evolve (Ivanov et al., 2017). In service-based industries, the interactions and activities of robots differ greatly and these differences are critical. Robots can perform a range of complex tasks and provide specialized services, completing tasks that take longer for humans to perform.

It is crucial for service organizations to understand and acknowledge the role that robots will play in their businesses and how it will affect their customers, to ensure that everyone is satisfied during this emerging trend (Lukanova & Ilieva, 2019). It is widely believed that tourists are not opposed to new technologies and that any dissatisfaction that may arise will not be due to the acceptance of new technologies, but because the expected smart experiences are not yet available (Murphy et al., 2020). On the other hand, these new technologies are seen as highly intriguing and it is believed that they can bring added value to hotels. The most intriguing and valuable technologies are considered to be robotics, virtual reality, and voice recognition applications, which are among the latest advancements in technology.

Digitalization, robotization, and new technological advancements are developments that can significantly impact the tourism industry's supply chain. In this context, devising strategies to address the following issues will aid in attracting more customers to the tourism supply.

- Digital marketing: The use of digital technologies can enhance the marketing of tourism products and services, thereby reaching a wider customer base.
- Improved service quality: The implementation of robotization and digital technologies can improve the efficiency and service quality of the tourism industry's supply chain.
- Digital reservations: Utilizing digital technologies can simplify the reservation process, making it easier for customers to book tourism services.

- Multi-channel sales: The adoption of digital technologies can enable the tourism industry to sell its products and services through multiple channels, thereby reaching a broader customer base.
- Digital destination management: The use of digital technologies can facilitate the management and planning of tourism services, helping the industry attract more customers.

In the context of smart hotels, new-generation technologies, and robotization can bring about several advancements in the areas of tourism, hotel management, and food services

- Smart rooms: Digital technologies can help make rooms smart and configure them according to customers' wishes.
- Smart energy management: Digital technologies can help reduce costs and reduce environmental impacts by increasing energy efficiency.
- Smart food and beverage service: Digital technologies can help make food and beverage services more effective and efficient.
- Digital check-in/check-out: Digital technologies and robots can help make check-in/check-out faster and more efficient and increase customer satisfaction.
- Smart tourism management: Digital technologies can help make tourism management more effective and efficient.
- Robotic service attendants: Robots can assist customers in food and beverage services, tasks such as cleaning and maintenance, and check-in/check-out.
- Augmented reality and virtual reality technologies: Augmented reality and virtual reality technologies can help increase experiences and increase customer satisfaction in tourism and hospitality

Advancements in next-generation technologies and robotization can enhance the speed, efficiency, and customer-centricity of services in the tourism, hospitality, and food services sectors. The implementation of the smart hotel concept can bring several benefits, including increased customer satisfaction, reduced costs, and a reduced environmental impact through the integration of digital technologies in the fields of tourism, hospitality, and food services. However, it is important to note that these technologies must be effectively managed and integrated with human interaction for optimal results.

The integration of next-generation technologies in the tourism, hotel, and food service industries may have some implications on the operations of these industries and the overall customer experience:

- Improved service quality: Digital technologies and robotization can help businesses across industries improve efficiency and service quality.
- Transformation for workers: Robotization can help workers reduce their workload and focus more on quality and speed, but may also involve the risk of some workers being replaced by robots.
- More opportunities: Digital technologies and robotization can create more opportunities for entrepreneurs looking to invest in the tourism, hotel, and food service industries.
- Digitalization: Digital technologies can help businesses in the tourism, hotel, and food service industries digitize and reach more customers.
- Greater security and privacy: Digital technologies can help keep customers' data more secure and protect their privacy.

These technological advancements can aid in formulating strategies for the future of the tourism, hotel, and food service industries, thereby ensuring their long-term success. The speedy growth of digital technologies offers more efficient and effective service opportunities in hotels and food and beverage services in the tourism industry. In particular, the implementation of smart robots can speed up the check-in and check-out procedures in hotels and provide quicker and more convenient service in food and beverage services, enhancing the competitiveness of the tourism sector and boosting customer satisfaction and loyalty. As a result, there is a need for a better comprehension and progression of the relationship between tourism and digital technologies.

Finally, the contributions of quantum robot technology, another new generation technology, to the tourism sector are also considered among the important changes that will occur in the future. Quantum computers are a technology that combines sensors, the internet, and other tools, which are programmed to process information faster and more efficiently than conventional computers and robots. This technology has the potential to bring many benefits to the tourism industry. For example, quantum computers can help travel and tourism businesses better analyze customer preferences and demands using advanced technologies such as AI and machine learning. This can result in improved service quality and efficiency.

Quantum sensors and the internet have the potential to improve safety and quality in the tourism sector. Furthermore, the use of quantum robots can help businesses to be more efficient and effectively manage their resources in the industry. Although quantum robots are not yet widely adopted in the tourism sector, businesses are starting to recognize the potential benefits of quantum technologies. As these technologies become more advanced and widely used, they are likely to bring even more benefits to the tourism industry. However, it is important to note that quantum technologies are still in their early stages of development and need to be properly regulated. The future development of quantum technologies is expected to bring even more advancements to the tourism sector, leading to more advanced and intelligent tourism systems. The use of quantum robots can also help businesses to optimize the use of time and resources

Quantum robots are still in the early stages of adoption in the tourism industry, but tourism businesses are starting to recognize their potential benefits. The wider use of quantum technologies in the industry may bring additional benefits over time. However, it is important to keep in mind that these technologies are still developing and their implementation needs to be properly regulated. In the future, the continued development of quantum technologies will have a significant impact on the tourism sector, leading to even more advanced and smart tourism systems. The use of quantum robots can help businesses to be more efficient and optimize the use of time and resources. Despite their potential, quantum robots are not yet widely used in the tourism industry, but the recognition of their benefits is increasing

Tourism businesses are beginning to recognize the potential benefits of quantum technologies, and their wider use in the industry may bring additional benefits over time. However, it is important to remember that quantum technologies are still in their early stages of development and need to be properly regulated. The future development of these technologies will greatly enhance the tourism sector, leading to more advanced and intelligent tourism systems. Despite their potential, quantum technologies are not yet widely used in the tourism sector. Nevertheless, tourism businesses are starting to evaluate the potential benefits of these technologies. It should be noted that their implementation needs to be properly regulated to ensure their proper use and development. The development of quantum technologies will continue to contribute to the advancement of the tourism sector, leading to even more sophisticated and smart tourism systems.

SUGGESTIONS

The following suggestions can be made regarding the effects of robotization and innovative technologies on the tourism, hotel, and food service sectors:

- Industry leaders should carefully evaluate the impacts of robotization and digital technologies and strive to understand how these technologies can benefit their businesses.
- Businesses should prioritize investments in up-to-date and effective technologies that meet the needs and expectations of customers
- Employee training should be given priority, and employees should be educated about robotization and the use of digital technologies.
- In addition to robotization and digital technologies, businesses should also invest in sustainable and environmentally friendly solutions.
- The security and protection of customers' privacy should be a top priority for businesses when using robotics and digital technologies

By following these recommendations, businesses in the tourism, hotel, and food service sectors can enhance customer satisfaction by maximizing the advantages of robotization and innovative technologies.

In the future, it may be advisable to conduct the following academic studies on robotization and digital technologies in the tourism, hotel, and food service sectors:

- A comprehensive analysis of the effects of robotization and digital technologies on the tourism, hotel, and food service industries.
- An investigation of how robotization and digital technologies enhance service quality in accordance with customer expectations and needs.
- An examination of the impacts of robotization and digital technologies on employees, particularly focusing on employee training solutions.
- An investigation of how a sustainable tourism and environmentally friendly approach can be integrated with robotization and digital technologies.
- An exploration of how to ensure the security and privacy of customers in the context of digital technologies and robotization processes

Such studies can provide valuable insights and guidance for businesses in the tourism, hotel, and food service industries and can uncover crucial strategies for the future of these industries.

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KEY TERMS AND DEFINITIONS

AI: Artificial Intelligence involves creating computer systems with human-like intelligence capabilities.

AR: Augmented Reality involves overlaying digital information on the real-world environment viewed through a device such as a smartphone or a computer.

Chatbot: A computer program that simulates a conversation with human users using text or voice-based interactions

Next-Gen Technology (NGT): NGT refers to cutting-edge advancements and innovations in various fields that aim to improve efficiency and provide new solutions. It includes technologies such as AI, 5G, IoT, quantum computing, robotics, and others.

SeviceBots: Robots designed to support and serve people through physical and social interactions.

Smart Technologies: Certain products and services that add value to the tourist experience by promoting higher interaction, **co**-creation, and personalization, using technology that enhances the experience.

VR: Virtual Reality is a computer-generated environment that can be interacted with using special equipment such as stereo-imaging goggles.

ARTICLES FOR FACULTY MEMBERS

AUTOMATED SOLAR AND ELECTRIC COMPOST BINS FOR THE TOURISM AND FOOD & BEVERAGE (HOTEL) INDUSTRIES

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The soft side of QFD: a comparative study on customer requirements' prioritization in the food sector

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Abstract

Despite its large popularity, the Quality Function Deployment (QFD) method has been the object of numerous studies addressing the problem of the assessment and prioritization of customer requirements. Nevertheless, a comparative analysis of these approaches to investigate their practical usability is scarcely discussed. This paper aims at filling this gap by means of a practical case study at a manufacturer in the food sector, where five of the most common approaches used to augment the House of Quality (HoQ) were analyzed and the results were compared. To achieve such a goal, semi-structured questionnaires were developed to capture consumers' preferences and expectations. The outputs of this study contribute to a better understanding of the potential and limitations of the examined approaches in order to address practitioners and companies in decision-making processes and resources allocation. Moreover, the article can serve as a reference for further investigations in the development of food products, where both intrinsic and extrinsic qualities need to be addressed.

Keywords
Quality Function Deployment (QFD), Kano Model, Analytic Hierarchy Process (AHP), Analytic Network Process (ANP), Decision Making

1. Introduction

Nowadays the globalized market, as well as the ever-increasing speed of companies in putting new products on the market, are making profitability and competitiveness more difficult for companies. Improving the quality of their products is a challenging task for engineers who have to balance the need to satisfy the customers' expectations with the company's bottom line (Haber et al. 2018). This is particularly true for Small and Medium-sized Enterprises (SMEs), which have difficulties in dealing with such issues, in addition to taking into account laws and regulations, e.g. health, safety and environmental requirements (Taticchi et al. 2010; Dror et al. 2012; Munir et al. 2014; Lombardi and Fargnoli 2017). The capability of a product to satisfy certain requisites in an appropriate way before its market-launch represents a key factor in product development activities. As noted by Burke et al. (2002), if decision-makers articulate what a customer requirement means ineffectively, an incorrect assessment of the importance of that demand occurs. In such a context, the Quality Function Deployment (QFD) method (Akao 1990) plays a primary role in assessing and improving the quality of a product or service before it is put on the market. In details, it facilitates the decision-making process allowing manufacturers a better understanding of the needs and expectations of the customers as to translate them into technical characteristics. The traditional QFD method is based on a four-phase approach (Figure 1) able to satisfy customers by translating their demands into design targets and quality assurance points.
The core of the method is the set of matrices called the "House of Quality" (HoQ), that is based on a cause-effect mechanism, which relates the Customer Requirements (CRs) (the so-called "whats") with Engineering Characteristics (ECs) (the so-called "hows") by means of a relationship matrix (Fargnoli and Sakao 2017). Additionally, the assessment of the "hows" is provided (obtaining the so-called "how-muches"), while mutual comparisons can be carried out by a correlation matrix ("the roof of the house"), as well as a benchmarking analysis (Figure 2).Despite its large diffusion, the QFD has been criticized for some weaknesses mainly due to the assessment criteria used in the HoQ, that can lead both to an erroneous evaluation of the qualitative characteristics and attributes, as well as to their incorrect prioritization (Chen et al. 2013; Vinayak and Kodali 2013; Zhang et al. 2015). As remarked by Kannan (2008), the inherent vagueness and impreciseness of the traditional HoQ is mainly due to: the type of inputs, which are often provided in the form of linguistic data; the impreciseness in translating qualitative CRs into ECs; and the resulting vagueness in defining the correlation measures among ECs.

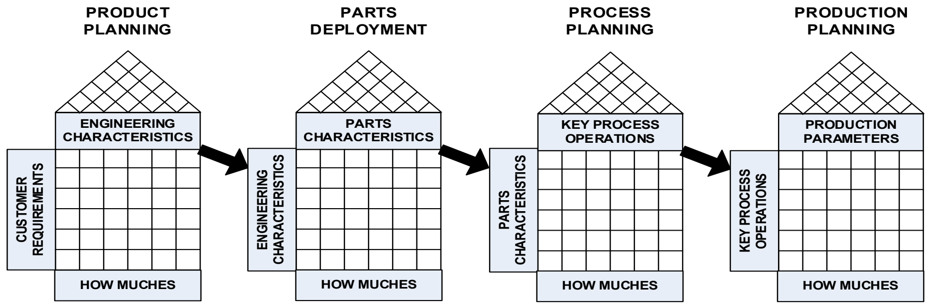

Figure 1. Scheme of the four-phase QFD (adapted from (Akao, 1990)).

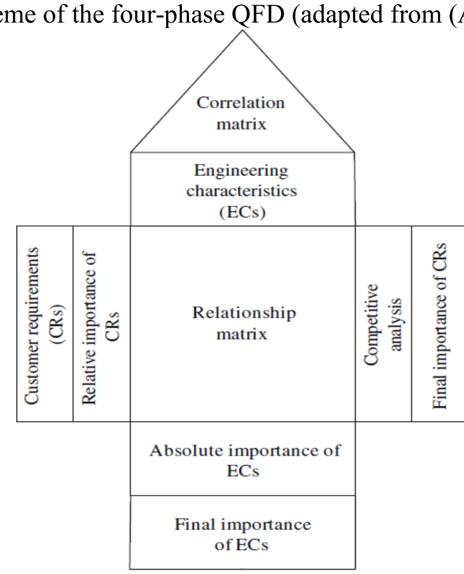

Figure 2. Scheme of the traditional House of Quality (adapted from (Akao, 1990)).

Accordingly, a considerable number of studies proposing possible improvement solutions to reduce this "softness" of the HoQ can be found in the literature (Shen et al. 2001; Xie et al. 2003; Zaim et al. 2014; Zhang et al. 2015; Zheng et al. 2016; Haber et al. 2020). For instance, Nahm et al. (2013) while discussing the limitations of the existing approaches to properly gain the final importance ratings of CRs, focused on capturing the customers' incomplete or uncertain perceptions on the relative importance of the CRs. Franceschini et al. (2015) reviewed the most diffused techniques for the prioritization of the CRs, underling the difficulties that can arise when the formulation of the customers' preference ordering is provided. To solve this problem, they proposed a novel approach based on Yager's Algorithm (Yager 2001). In addition, Sivasamy et al. (2016) proposed a review of the literature on the development and application of advanced models of QFD. They analysed several well-known HoQ supporting tools, providing a qualitative assessment mainly based on their procedural and computational complexity and pointing out that despite enhancing the precision and accuracy of the results, most advanced models of QFD require excessive efforts that limit their practical usability. On one hand, these studies provided accurate analyses concerning the HoQ's limitations and its possible augmentations. On the other hand, it can be noted that different studies adopted different approaches, while a comparative and practical evaluation of the effectiveness of these supporting tools is scarcely discussed. Consequently, practitioners have difficulties when selecting the proper tools to improve the HoQ for their specific goal. Hence, the present study is an attempt to fill this gap by investigating the customer requirements' prioritization problem by means of a case study approach. To do so, the paper addresses the following research question:

RQ. Which approach is more fitting to prioritize the CRs depending on the goal of the analysis and what are the benefits and limitations of each?

With this goal in mind, and based on the studies mentioned earlier, we analyzed and compared some of the most diffused approaches to augment the HoQ's performances through a case study at the same food manufacturer.

The remainder of the paper is structured as follows: Section 2 briefly exposes our research approach, which is based on a comparative analysis in the food sector. Then Section 3 describes these analyses, and the results are shown and discussed in Section 4. Lastly, Section 5 concludes the article and reflects on future research work.

2. Research approach

As mentioned above, numerous studies have investigated the possibility of augmenting the HoQ to reduce its limitations when assessing CRs, and most of them highlighted among others the following types of QFD supporting tools:

1. Methods to categorize CRs, such as the Kano model (Kano et al. 1984). This method is widely recognized as one of the most effective tools for identifying the value perceived by customers concerning the various CRs. It allocates them to five fundamental quality categories: Must-be (M), One-dimensional (O), Attractive (A), Indifferent (I) and Reverse (R). The categorization derives from functional and dysfunctional inquiries where the customer's reactions are identified through specific questionnaires (Matzler and Hinterhuber 1998).
2. Methods to prioritize CRs using pairwise comparisons, e.g. the Analytic Hierarchy Process (AHP) and the Analytic Network Process (ANP) approaches (Saaty 1980; Saaty and Sodenkamp 2008). Both AHP and ANP allow engineers to select the most appropriate solution to a complex problem by decomposing it in a systematically and hierarchically (Ho 2008; Fargnoli et al. 2020; Fargnoli and Haber 2019).
3. The fuzzy set theory to overcome uncertainty problems due to the use of linguistic variables (Büyüközkan and Feyzioğlu 2005; Bevilacqua et al. 2006; Liu 2009). The Fuzzy Logic approach deals with the uncertainty deriving from the imprecision and vagueness of the qualitative and subjective definitions of CRs (Abdolshah and Moradi 2013). Such an approach is usually applied to augment the AHP or ANP methods.
4. Tools aimed at the prioritization of preference orderings of CRs (Nahm et al. 2013; Franceschini et al. 2015). An ordering-based approach based on Yager's theory of aggregation allows engineers to address the problem of aggregating importance orderings of multiple decision-makers with respect to a set of possible alternatives (Yager, 1993; Wang and Tseng 2011; Chen et al. 2013; Zheng et al. 2016). In particular, we focused on Thurstone's Law of Comparative Judgement (LCJ) (Thurstone 1927), introduced by Franceschini and Maisano (2015), to aggregate the CRs' judgments into a continuous interval scale (Haber and Fargnoli 2019).

Needless to say, the above list cannot be considered exhaustive, since a plethora of studies have dealt with the analysis and application of QFD supporting tools in different sectors. Based on the previous analysis, we selected five different approaches that correspond to the main followed solutions to augment the HoQ: in Table 1, the list of the method is proposed, as well as the criteria adopted for the prioritization of CRs and study we used as a reference for the method's application.

Table 1. List of the tools used in the case study

Tools	CRs prioritization criteria	References
ANP	Assessment of the correlation relationships	Lam 2015
Fuzzy Logic	Translation of linguistic preferences into quantitative values	Liu 2009
Kano	CRs importance based on Customer Satisfaction	Matzler and Hinterhuber 1998
Thurstone's LCJ	Preference ordering through an ordinal scale	Franceschini and Maisano 2015
Fuzzy AHP	Hierarchization based on multiple sets of values	Abdolshah and Moradi 2013

It has to be noted that these tools do not represent all the solutions that have been proposed in the scientific literature. We limited our selection to some of the most studied ones, as examples of different ways of improving the HoQ's weaknesses concerning the assessment and prioritization of the CRs. Similarly, the analysis of advanced mathematical models, such as the fuzzy goal programing (FGP) approach (Chen et al. 2017) or the evidential reasoning (ER) based QFD method (Chin et al. 2009), are beyond this paper.

The comparative analysis of these tools was carried out through their application in a case study at a food manufacturer. The choice of the case study is due to two main reasons: the size of the manufacturer, as our study is aimed at providing easy-to-handle hints for SMEs; and the complexities that reside in properly interpreting the consumer's requirements given the sensory characteristics of the food product (Vatthanakul et al. 2010; De Pelsmaeker et al. 2015), which make the description of CRs vaguer and imprecise (Dolgun and Koksal 2017).

More in detail, the study was performed in collaboration with a small-sized sugar confectionery manufacturer seeking to improve the quality of its chocolate bars. Six types of bars are produced: the basis can be made by milk chocolate or dark chocolate, and they can include pieces of almonds or nougats. In particular, the concerned product in this study is a milk chocolate bar mainly consumed as a snack, which is sold in pieces of 100 grams at company shops and through retailers. The company was interested in understanding its customers' preferences for this type of product to address its future production. The study was carried out involving a focus group of experts, including a company technician, an expert in food engineering, and an expert in food science. As per the customers' interviews, a group of 120 university students, who are chocolate bar consumers, was involved. They were divided into 3 groups and interviewed separately to avoid any bias: group A (20 people); group B (50 people), and group C (50 people).

3. Case study

The first step of the study consisted of determining the Customer Requirements (CRs) and Engineering Characteristics (ECs). In details, the CRs' definition was obtained by means of semi-structured individual interviews to group A. As for the Engineering Characteristics (ECs), they were established in cooperation with a group of experts (Table 2).

Table 2. List of the selected customer requirements (CRs) and engineering characteristics (ECs)

Customer Requirements	Engineering Characteristics
CR 1 – Rich and intense taste	EC 1 – Fat content
CR 2 – Reduced fats	EC 2 – Sugar content
CR 3 – Presence of dried fruits	EC 3 – Dried fruits content
CR 4 – Easiness to chew	EC 4 – Quantity of chocolate
CR 5 – Easy to store when opened.	EC 5 – Dough smoothness
CR 6 – Pleasing appearance	EC 6 – Size of dried fruits
CR 7 – Adequate size.	EC 7 – Presence and shape of the notches
CR 8 – Affordable price	EC 8 – Chewiness
	EC 9 – Format
	EC 10 – Type of wrapping (packaging)
	EC 11 – Price
	EC 12 – Surface characteristics
	EC 13 – Gloss
	EC 14 – Aroma
	EC 15 – Texture

Then, to complete the collection of data to use as input for the application of the selected tools, a questionnaire was developed in cooperation with the company's experts and submitted to group B. The members of this group were asked to grade the importance of each CR using a Likert scale (Likert 1932), ranging from 1 (not important) to 5 (extremely important). The customers were asked to rate their satisfaction levels according to the company's product as well as to two equivalent products produced by two main competitors: this allowed the company to measure its performance on the market vis-à-vis the CRs. The obtained information was measured against a target value set by the experts to identify the possible improvement margins.

Afterwards, a different questionnaire was used involving group C to assess their satisfaction as per Kano et al. (1984), and to obtain a pairwise comparison of the CRs as to evaluate the importance of each CR compared to the others (Liu 2009; Ho et al. 2012). The latter was performed by means of an importance scale ranging from 1 (CR_i and CR_j are of equal importance) to 9 (CR_i is significantly dominant compared to CR_j). This allowed us to obtain data for the implementation of the AHP and ANP approaches by means of the criteria defined by (Kamvysi et al. 2014). For the use of the fuzzy logic, we opted for Triangular Fuzzy Numbers (TFNs) given their easy handling and manipulation (Table 3).

Table 3. Crisp and fuzzy scales

Linguistic variables	Rating Scale	Equivalence in Fuzzy numbers	
		TFNs	Reciprocal TFNs
Equally important	1	(1, 1, 1)	(1, 1, 1)
Intermediate	2	(1, 2, 3)	(1/3, 1/2, 1)
Moderately more important	3	(2, 3, 4)	(1/4, 1/3, 1/2)
Intermediate	4	(3, 4, 5)	(1/5, 1/4, 1/3)
Strongly more important	5	(4, 5, 6)	(1/6, 1/5, 1/4)

Intermediate	6	(5, 6, 7)	(1/7, 1/6, 1/5)
Very strongly more important	7	(6, 7, 8)	(1/8, 1/7, 1/6)
Intermediate	8	(7, 8, 9)	(1/9, 1/8, 1/7)
Extremely more important	9	(8, 9, 10)	(1/10, 1/9, 1/8)

3.1. Traditional House of Quality

The traditional QFD method was applied, taking into account the abovementioned information and the Absolute Importance (AI) of each EC was deduced using (1).

$$AI_j = \sum_{i=1}^{8} RI_i \times S_{ij} \tag{1}$$

Where 'j' indicates the column (EC), 'i' indicates the row (CR), RI is the Raw Importance and S_{ij} is the relationship score between EC_j and CR_i, rated 1, 3 or 9 (ReVelle et al., 1998). Then, the company's product was compared to two competitors producing equivalent chocolate bars. Consequently, the gaps separating the company from its desired performance levels were defined by the Improvement Ratio (IR). This results in an HoQ where the CRs are defined by their Raw Weights (RW) (Figure 3).

	RW	Relative RW	*CR Ranking*	EC 1	EC 2	EC 3	EC 4	EC 5	EC 6	EC 7	EC 8	EC 9	EC 10	EC 11	EC 12	EC 13	EC 14	EC 15
CR 1	5.61	11.88%	*3*	9	9	9	9	3	3					9		3	1	9
CR 2	5.01	10.59%	*4*	9	9	9	9		3					3	1	1	3	9
CR 3	3.92	8.30%	*5*	3	1	9	3	3	9	3	9				3		1	9
CR 4	3.87	8.20%	*6*	3	3	9	9	9	9		9							9
CR 5	3.51	7.43%	*8*	3	3	9	9		9	9		9	9					
CR 6	5.97	12.62%	*2*	3	1	9	9	3	9	9		9	9		9	9		
CR 7	3.84	8.13%	*7*									9	9	9				
CR 8	15.53	32.85%	*1*	9	9	9	9		9			9	9	9			3	3

	EC 1	EC 2	EC 3	EC 4	EC 5	EC 6	EC 7	EC 8	EC 9	EC 10	EC 11	EC 12	EC 13	EC 14	EC 15
Absolute Importance (AI)	287.12	267.34	390.74	367.20	81.36	327.02	97.04	70.16	259.57	259.57	239.83	70.47	75.54	71.13	212.32
Relative Absolute Importance	9.33%	8.69%	12.70%	11.94%	2.64%	10.63%	3.15%	2.28%	8.44%	8.44%	7.80%	2.29%	2.46%	2.31%	6.90%
EC Ranking	*4*	*5*	*1*	*2*	*11*	*3*	*10*	*15*	*6*	*6*	*8*	*14*	*12*	*13*	*9*

3.2. Kano model implementation

As mentioned above, Kano's quality categories were deduced from the questionnaires. Thus, the Customer Satisfaction Coefficient for satisfaction (CSC_{SI}) and dissatisfaction (CSC_{DI}) were calculated using (2) and (3). Then the Improvement Ratio was defined by means of (4), where "k" represents a correction coefficient related to the Kano categories (Matzler and Hinterhuber 1998) as shown in (5).

$$CSCSI = \frac{A+O}{A+O+M+I} \tag{2}$$

$$CSCDI = -\frac{O+M}{A+O+M+I} \tag{3}$$

$$IR_{adj} = (IR_0)^{\frac{1}{k}} \tag{4}$$

$$k = \begin{cases} 0.5, & Must-be\ quality \\ 1, & One-dimensional\ quality \\ 2, & Attractive\ quality \\ 3, & Indifferent\ quality \end{cases} \tag{5}$$

The adjusted IR is utilized in (3), leading to the adjusted RWs of each CR, which are then used to complete the HoQ (the results are shown and discussed in Section 4).

3.3. Fuzzy Logic implementation

As mentioned before, we adopted the Fuzzy Logic approach based on the criteria proposed in Table 3 and the TFN scale was used to estimate the results of the CRs comparisons. This allows us to construct a fuzzy pairwise-comparison matrix for each customer, and finally, an average fuzzy value is obtained to construct a CR comparison matrix (Table 4). The resulting TFNs are then normalized.

3.4. ANP implementation

The ANP method consists of three main stages: developing the network diagram, generating the matrix and determining the system elements' priorities. Hence, in accordance with the model proposed by Liu and Tsai (2012) in a QFD context the network representation can be adapted as follows.

Table 4. Fuzzy CR comparison matrix (excerpt of 3 CRs)

	CR 1			CR 2			CR 3		
CR 1	1.00	1.00	1.00	4.16	4.90	5.64	2.80	3.42	4.05
CR 2	0.18	0.20	0.24	1.00	1.00	1.00	1.45	1.80	2.16
CR 3	0.25	0.29	0.36	0.46	0.56	0.69	1.00	1.00	1.00

The first step is the definition of the degree of importance of the CRs with respect to the goal, w_{21}, assuming there are no dependencies among them (Lam 2015). The inner-dependencies of the CRs is then determined as well as the inner-dependencies of the ECs. Then, the importance levels are calculated with respect to each of the 8 CRs, which leads to w_{32}. Using the formula (6), the overall priorities of the ECs are then computed by multiplying the four resulting weight vectors: (the ensuing results are shown and discussed in Section 4).

$$w_{ANP} = w_{21} \times w_{22} \times w_{32} \times w_{33} \quad (6)$$

3.5. LCJ implementation

The LCJ implementation is based on the approach proposed by Franceschini and Maisano (2015). Accordingly, each CR is characterized by a normal distribution $CR_i \sim N(\mu_i, \sigma_i^2)$, where "μ" is the mean and "σ" the standard deviation. Per Thurstone (1927), a CR is characterized by a variance which mirrors the CR-to-CR variability (7), where "ρ_{ij}" is the correlation between CR_i and CR_j.

$$CR_{ij} = CR_i - CR_j \sim N\,(\boldsymbol{\mu_{ij}} = \mu_i - \mu_j,\ \boldsymbol{\sigma_{ij}^2} = \sigma_i^2 + \sigma_j^2 - 2\,\rho_{ij}\,\sigma_i\,\sigma_j) \quad (7)$$

First, the customers' importance level attribution is morphed into a linear ordering known as a rank-order data (Figure 4). The CR comparison matrix is derived from the linear ordering previously established by using the practical response mode, where a preferred CR over another is noted "1" (otherwise "0") and an equal importance level is noted "0.5" (Table 5).

	Importance Level				
	Not important	Little important	Important	Very important	Extremely important
CR 1			X		
CR 2		X			
CR 3					X

Linear Ordering
CR 3 > CR 1 > CR 2

Figure 4. Linear ordering example of the CRs (excerpt from an interviewed customer for 3CRs)

Table 5. CR comparison matrix (excerpt of 3 CRs)

	CR 1	**CR 2**	**CR 3**
CR 1	0.5	1	0
CR 2	0	0.5	0
CR 3	1	1	0.5

Subsequently, the paired comparison matrices are aggregated into a single Frequency matrix (F) which denotes the number of times a row-entry CR_i, has been preferred over a column-entry CR_j. Based on this, a Probability matrix (P) is created as per (8), where F_{ij} is an element of the i[th] row and the j[th] column of F and N is the total number of customers, N = 50 .

$$P_{ij} = \frac{F_{ij}}{N} \quad (8)$$

The Probability matrix (P) can then be interpreted though a standardized variable z_{ij} (9), which leads to the Standardized matrix (Z).

$$z_{ij} = \frac{CR_{ij} - \mu_{ij}}{\sigma_{ij}} \tag{9}$$

where:

$$\mu_{ij} = \mu_i - \mu_j \tag{10}$$

$$\sigma_{ij} = \sqrt{(\sigma_i^2 + \sigma_j^2 - 2\,\rho_{ij}\,\sigma_i\,\sigma_j)} \tag{11}$$

Moreover, in a paired judgement scheme where the evaluation of one CR has no effect nor influence on the evaluation of another CR, the correlation factor ρ_{ij} is very low and even null (Franceschini and Maisano, 2015). Furthermore, each CR represents different requirement concepts and the number of responding customer is adequate. This allows assuming a constant and null correlation factor, as per Thurstone (1927): $\rho_{ij} = \rho = 0$, for all row and column entries. Consequently, the Thurstone scale's values, ranging from 1 to 5, of each column element, CR_j, are determined as the mean of each column's elements of (Z). The resulting scale values represent the weights (importance) of the CRs which lead to the HoQ augmented by Thurstone's LCJ.

3.6. Fuzzy AHP implementation

In addition to the application of tools belonging to the four approaches discussed in Section 2, a combination of them is also possible as illustrated in numerous studies. In particular, the fuzzy approach is incorporated to improve the transparency of the CRs and minimize inconsistencies by enhancing the conventional AHP approach (Kwong et al., 2003; Saaty and Sodenkamp, 2008; Kamvysi et al., 2014).

The first step of such an approach is the same as in Section 3.3. This allowed us to define the Fuzzy CR comparison matrix and the normalized CR fuzzy comparison matrix. Then, the average of the row elements of this matrix are calculated using (15) to define the column vector where C_{ik}^1 characterizes the grading of each CR's importance 'i' (i=1...n). A consistency check follows by multiplying each element in column 'j' of the normalized CR fuzzy AHP matrix by C_{ik}^1 and then dividing the sum of the elements of row 'i' by C_{ik}^1 to yield another column vector, i.e. the $\hat{C}_{CR}$ crisp matrix (Ho et al. 2012). The consistency ratio is finally deduced (where RI (n) is the random index value dependent on the number of RSPs, 8 in this context and hence RI (8) = 1.41 (Ho et al. 2012) as:

$$CR = \frac{CI}{RI\ (n=8)} = 0.0616 \tag{12}$$

Similarly, the CRs were grouped into four categories: alimentary characteristics, practicality, aesthetics, and economical aspect. The same approach as the CRs was applied which led to the C_{cat} crisp matrix (Table 6).

Table 6. C_{CAT} crisp matrix.

Categories	**C_{CAT} crisp**	**C_{CAT} relative**
A. Alimentary characteristics (CR 1, CR 2, CR3)	2,50	62,52%
B. Practicality (CR 4, CR 5)	0,54	13,44%
C. Esthetics (CR 6, CR 7)	0,37	9,23%
D. Economical aspect (CR 8)	0,59	14,80%

Consequently, the HoQ augmented taking into consideration the importance levels obtained per the Fuzzy AHP method is obtained, where the final weight of each CR is calculated as per (13) and the results are shown and discussed in Section 4.

$$C_{FIN} = C_{CR} \text{ x } C_{CAT} \tag{13}$$

4. Discussion of results

The different approaches represent different ways to augment the performances of the HoQ in understanding and assessing CRs: the weights and the importance levels for each CR based on each approach are shown in Figure 5. These results bring to light the significant differences that occur depending on the approach used to augment the HoQ. For instance, on the one hand, Thurstone's LCJ and the Kano model provide slight differences among the various CRs: i.e. CRs vary in a small range of values, 15,35% (Thurstone's LCJ) and 14,95% (Kano). On the other hand, the other approaches allow a higher level of differentiation: i.e. 31,83% (Fuzzy), 31,31% (ANP) and 47,60% (fuzzy AHP). Secondly, even though the Thurstone's LCJ approach did not show any significant preference (i.e. a CR much more important than the others), it allows engineers to differentiate the CRs. In other words, CRs with similar weights were not found, while some strong resemblances can be observed for the other methods.

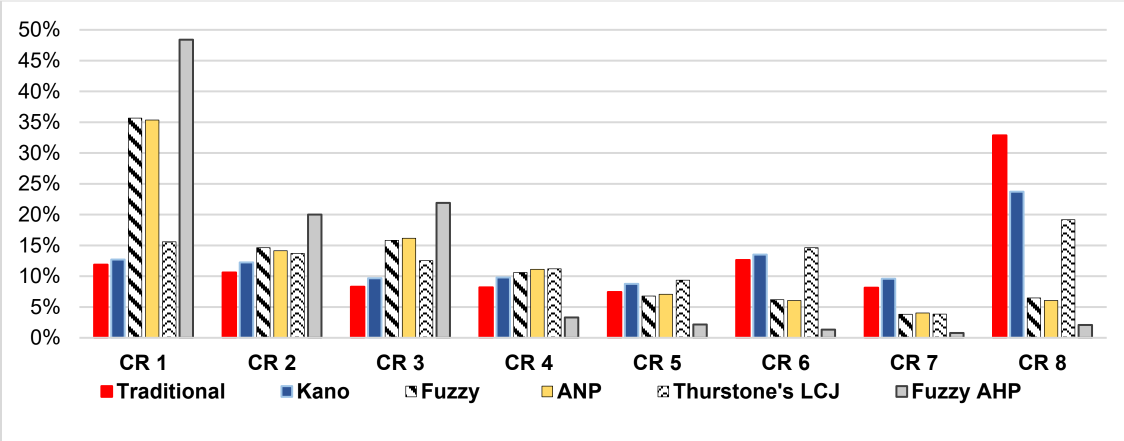

Figure 5. Variation of the importance of the CRs in function of the applied methods.

For example, in the traditional HoQ the differences among CR3 (8,30 %), CR4 (8,20 %) and CR7 (8,13 %) are minor, as well as in the Kano model (CR3 (9,66 %), CR4 (9,81 %) and CR7 (9,59 %)). Moreover, the ranking of the CRs also varies from one approach to another, as shown in Table 7.

Table 7. CR rankings according to each method.

	Traditional	**Kano**	**Fuzzy**	**ANP**	**Thurstone's LCJ**	**Fuzzy AHP**
CR 1	3	3	1	1	2	1
CR 2	4	4	3	3	4	3
CR 3	5	6	2	2	5	2
CR 4	6	5	4	4	6	4
CR 5	8	8	5	5	7	5
CR 6	2	2	7	6	3	7
CR 7	7	7	8	8	8	8
CR 8	1	1	6	7	1	6

More in detail, on the one hand, the Fuzzy, Fuzzy AHP and ANP approaches provided very similar results: i.e. they emphasize more some requirements than others in a similar manner (for instance CR8 has a high impact according to all the three tools, as well as CR1 has a low one). On the other hand, the traditional HoQ and the Kano model showed close analogies. It has to be noted that Thurstone's LCJ approach provided a different ranking of CRs from the ones proposed by the other approaches (yet a few similarities can be found with the ANP and Fuzzy AHP methods).

Considering the three most important CRs per each method, the same bias in favor of CR1 can be found in all of them. However, the other priorities change significantly whereas, in the traditional, Kano and Thurstone's LCJ models, the non-sensory CRs (e.g. CR8 - Affordable Price) are brought forth as they are considered separately from the other CRs. However, the fuzzy, ANP and fuzzy AHP models consider the correlations between the non-sensory and sensory requirements (e.g. CR1 - Rich and intense taste) allowing a more comprehensive and coherent assessment of the CRs. Thus, if a company in the food sector decides to satisfy the most relevant customer demands comprehensively, the latter methods can provide quite comparable results, allowing a holistic perception of customers' needs. On the contrary, if the company is interested in focusing more on marketing aspects rather than modifying the ingredients of the product itself, the traditional QFD, as well as Kano's model and Thurstone's LCJ approaches can provide useful information in terms of competitiveness. It has to be noted that the latter approach also provides a differentiation between each CR and the others; hence its use is suggested when decision-makers need a more complete ranking of CRs. Similarly, the importance levels of each EC were evaluated, and their mutual comparison denotes a lower variability compared to the one associated with the CRs. For example, EC15 (texture) undergoes the most variation when the Fuzzy AHP method is applied, with an increase of almost 100% in importance compared to its initial value. Oppositely, EC10 (type of wrapping) and EC6 (size of dried fruits) become the least important as the Fuzzy AHP applied (Figure 6).

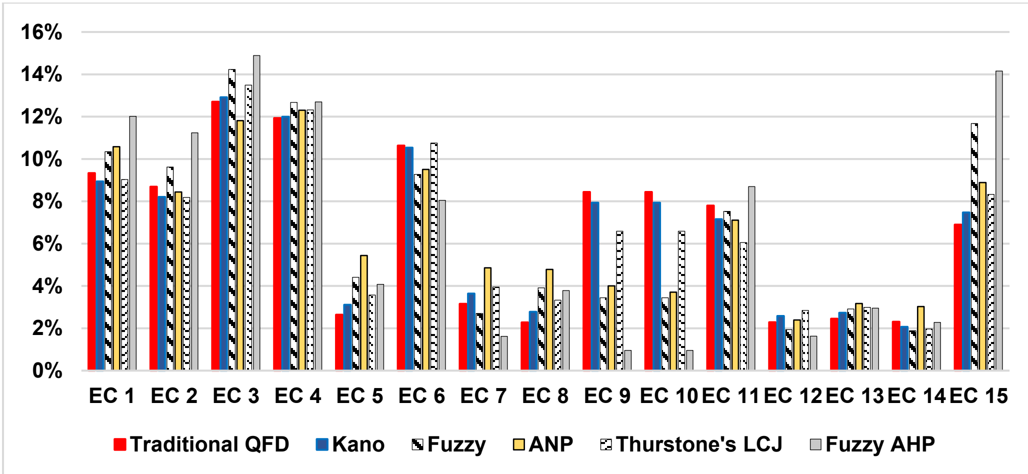

Figure 6. Variation of the importance of the ECs in function of the applied methods.

From the obtained results, no QFD supporting approach can be considered complete and adaptable to any product and context. Given that each approach presents its benefits and disadvantages, their use depends on both the manufacturer's resources and the goal of the analysis. As far as the former aspect is concerned, the Fuzzy AHP and the ANP approaches certainly require a more relevant effort; on the contrary, the application of the Kano model is simpler, while the computational effort for the use of the Thurstone's LCJ approach is directly related to the number of the CRs. When considering the goal of the application, in synthesis we can observe that:

- The Thurstone's LCJ approach provides a clearer ranking of customers' judgments, allowing engineers to differentiate each CR from the others;
- The Fuzzy and Fuzzy AHP allows engineers to better focus on sensorial attributes;
- Marketing aspects are better stressed by the Kano model and Thurstone's LCJ approach;
- When the goal of the analysis is to better understand the balance among all qualitative characteristics of the product, the ANP approach can provide results that are more thorough and comprehensive.

Accordingly, from a more general perspective, it emerged that fuzzy and hierarchical approaches are more accurate as they bring forward the importance of the subjective criteria that a quantitative assessment cannot capture. This accomplishes the research approach proposed by Dolgun and Köksal (2017), who used AHP to prioritize CRs from the customers' perspective and Kansei Engineering (KE) to better capture the customers' feelings. Conversely, since they need experienced users and require certain computational efforts, Thurstone's LCJ approach might represent a good solution especially when a preliminary feasibility analysis is needed while developing a new product. Furthermore, the study confirmed the difficulties in interpreting customer needs and expectations when dealing with a food product, envisaging the benefits that the use of the QFD can provide in this context. This is in line with the findings of the few studies that addressed such issues (de Fátima Cardoso et al. 2015). In fact, as argued by Benner et al. (2003), it is very difficult to interpret the consumer wishes properly, as this relies on the understanding of their perceived quality. Hence, when analyzing the quality of a food product both its intrinsic and extrinsic attributes need to be addressed (Ikeda et al. 2004). Based on this, despite its large popularity and potentials, the use of QFD is limited in the food sector (Bevilacqua et al. 2012). For this reason, our study can augment the knowledge the use of such a tool in capturing the customers' preferences for adequate decision-making when developing the food product.

Overall, even though the QFD supporting tools are largely examined in the literature, a comparative analysis among them is scarcely discussed. Hence, this study can certainly contribute to better understand the potential and limitations of the examined approaches. Since it was performed in a practical context and with the support of a multifunctional group of experts, the achieved results can be considered consistent and useful for practitioners. Moreover, the outputs of this study can also contribute to augment the scientific knowledge on the use of QFD, especially in the food sector. The results obtained confirm the difficulties that practitioners can find when dealing with the HoQ's "mechanism" and the ambiguity of qualitative assessment criteria (Burke et al. 2002; Olewnik and Lewis 2008; Raharjo et al. 2011). Still, they can guide engineers in selecting the proper approach depending on their sought goals and the availability of their resources. Besides these positive aspects, some limitations need to be outlined. Firstly, although the numerous studies reviewed, the number of supporting tools used cannot be considered exhaustive. We selected five of the main diffused approaches discussed in the literature to augment the effectiveness of QFD.

Nevertheless, other tools can certainly be found, such as the Design Structure Matrix (DSM) and the Domain Mapping Matrix (DMM) (Eppinger and Browning 2012), the Axiomatic Design (Carnevalli et al. 2010), the Spherical fuzzy QFD (SF-QFD) (Gündoğdu and Kahraman 2020), or the Hesitant Fuzzy QFD (Onar et al. 2016). Moreover, since the study was carried out in the food sector, the "qualitative" nature of the parameters used in the HoQ makes the assessment of their interdependencies more difficult (Benner et al., 2003). Thus, a larger number of customers involved in the study can provide more precise results, especially when using the ANP and the Thurstone's LCJ approaches.

5. Conclusions

Despite its global diffusion and large use, the QFD methods present some limitations especially concerning the evaluation and the prioritization of customers' needs. This article proposed a comparative analysis of some of the most well-known approaches that are used to address such a problem utilizing a practical case study at a company operating in the food sector. The results achieved have brought to light the different potentials of such approaches in maximizing the benefits of the HoQ and reducing its "softness", which mainly relies on the difficulties arising from the dependency on the human assessment abilities, i.e. the problem of transforming qualitative judgments into quantitative values by means of an ordinal scale. In summary, our study provides practical insights in addressing the use of the HoQ and several of its supporting approaches to better understand and prioritize customers' needs through a case-based research. Accordingly, the article can serve as a reference for further investigations in the food products' development, where both intrinsic and extrinsic qualities need to be addressed. However, to reduce the above-mentioned limitations further research work is needed. In particular, the application of the proposed approach in a different context, as well as its implementation with the support of a larger number of questionnaires (i.e. more customers involved) can certainly help in improving the validity of our practical findings.

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The use of intelligent automation as a form of digital transformation in tourism: Towards a hybrid experiential offering

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ABSTRACT

The purpose of this study is to explore the extent to which intelligent automation (IA) should be used to provide the best possible service quality and experience to customers, an area that needs further exploration. The study draws on an inductive qualitative inquiry from the supply side which has been rather overlooked despite its significant role in designing and shaping experiences. The data were gathered by conducting a total of 39 semi-structured interviews with tourism service providers in Cyprus. The findings revealed insightful information regarding human-IA tasks and interaction from a tourism provider perspective while stressing the cooperation between humans and IA within a service context. The importance of the human element, individual characteristics and key human capabilities are particularly stressed within a continuous digitally transformative industry. The paper concludes with theoretical contributions in regard to the experiential theoretical milieu, practical implications, and future research directions.

1. Introduction

Intelligent automation (IA) utilizes artificial intelligence to create smart processes that "think", function, and adapt on their own to deliver automated services, such as in the case of robots. In a technological framework of intelligent automation, Tussyadiah (2020) placed pervasive and intelligent robots at the overlap between artificial intelligence, the Internet of things, and robotics.

The physical and social distancing practices as a result of the COVID-19 pandemic, reinforced and intensified intelligent automation particularly in services. During the lockdown, industries in the service sector rushed to embrace automation processes. Businesses looked to the application of artificial intelligence (Coombs, 2020) to the extent of the human element being excluded from the delivery process and being replaced by (e.g.) robotic means (Cuthbertson, 2020). In fact, robots have attracted considerable attention from academics in recent years (Lu et al., 2020; Rampersad, 2020; Shin and Jeong, 2020; Tuomi et al., 2020; Tussyadiah et al., 2020), with researchers (such as, Lu et al., 2020; Webster and Ivanov, 2019) predicting that robots will have a profound impact on services in the future.

Studies have examined and revealed various impacts of such intelligent automation on the procedures of businesses, their employees and customers, with a number of both positive and negative influences being recorded (Lu et al., 2020; Rampersad, 2020). These can be summarized into certain risks, such as decreased opportunities for employment for humans and loss of control due to robot autonomy (Tussyadiah, 2020). Also, benefits that come in the form of increased productivity, efficiency, cost savings, and improved support for customers/users. Despite the overabundance of studies that have examined aspects of intelligent automation within service provision/experience (Yam et al., 2021; Park, 2020; Jörling et al., 2019; Mende et al., 2019), the question of "what level of intelligent automation is to be used to provide the best possible customer service quality and experience?" remains rather elusive. On one hand, we have evidence supporting the experiential value of new technology in services. Indeed, the importance of intelligent automation within the experiential milieu rests on the fact that it is connected with digital transformation which deals with the process of using digital technologies to create new (or modify existing) customer experiences (Kraus et al., 2021; Matarazzo et al., 2021). On the other hand, organizations may find it hard to find a balance between customer expectations and operational efficiency (Tuomi et al., 2021). Also, there are fears about technology particularly in the form of robots, eliminating

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and marginalizing the "human touch" within the service context (Christou et al., 2020). Therefore, there are still gaps linked to both the precise identification of human or machine services and answers to questions regarding how organizations should implement and manage new technological systems in their organizations (Loureiro et al., 2021).

A potentially suitable context for addressing such research gap is the tourism context. Within the last two decades, the tourism industry has adopted radical technological innovations and intelligent automation (Tussyadiah et al., 2020; Kuo et al., 2017). Literature suggests that tourism embraces both intangible/serviceable and tangible characteristics. Furthermore, it relies heavily on the human factor for the delivery of services, yet simultaneously uses new technology, such as in the form of robots and virtual reality (Flavián et al., 2021). Tourism, through its idiosyncratic nature that often entails high levels of human interaction, provides excellent opportunities for the investigation of human/automation linked phenomena. The need for – and importance of – this study is underpinned by the study of Tussyadiah (2020) who reviewed research into automation in tourism and proposed a relevant research agenda for preparing tourism for a more automated future. More specifically, the research questions that guided our study were, firstly: "Which aspects of the tourism experience can be enhanced with the application of intelligent automation?", and secondly, "How should humans and intelligent automation separate and/or merge their tasks to improve tourism service provision?" Despite the fact that certain tourism organizations continue to rely heavily on the human provision of exceptional service and hospitality to ensure an enhanced customer experience, intelligent automation has been adopted to ease procedures and enhance experiences. However, it may be argued whether aspects of intelligent automation (such as, robotic means) may – or should – replace human-linked characteristics within a service context. For instance, although there is evidence suggesting that robots may enhance the overall tourist experience, some firms may avoid the use of humanlike (otherwise referred to as anthropomorphic) robots to avoid feelings of eeriness that customers may experience (Blut et al., 2021). Furthermore, the adaptation of intelligent automation may strike as an antithesis to the very core of an industry that remains heavily reliant on human-delivered services, human interactions and hospitality offering (Lynch et al., 2021; Christou and Sharpley, 2019; Lashley, 2015).

This study takes into account the perspectives of people (that is, suppliers) in regard to intelligent automation in tourism, as presented in the recent research milieu (Akdim et al., 2021; Odekerken-Schröder et al., 2020; Park et al., 2021; Cha, 2020). More specifically, it delivers the perspectives of tourism suppliers who have been largely overlooked by academics despite their important role in the designing, shaping, and offering of customer value experiences. The importance of the study rests on the fact that it addresses gaps regarding the use of new technology in the service delivery process, and explores the extent to which it may be used by organizations that rely on service provision. Technology will remain vital for the expansion of the service economy (Huang and Rust, 2017). Intelligent automation will continue to change the way services are provided and the manner in which customers and firms interact with each other (van Doorn et al., 2017). All the same, the anthropocentricity of the service industry which rests on human attributes and human-linked service provision and qualities, such as empathy, is challenged through the implementation of such new technology (Christou et al., 2020). Service-linked organizations are in need of clear directions as to what extent they are to rely on technological means and human-led service in their service/experiential delivery process. Besides this, recent studies call for further insights regarding how organizations are to manage and implement such new technologies in their organizations (Loureiro et al., 2021). The theoretical discussion that follows places intelligent automation within an experiential tourism context. As explained in the following section, experiences are situated in the very core of the tourism domain since they impact on the perceptions, motivations, and attitudes of people, not least satisfaction, repurchase decisions, and loyalty towards organizations.

2. Intelligent automation within an experiential tourism context

Experiences are particularly important for specific industries, such as the general service sector, businesses that provide gamified services (Wolf et al., 2020), the events sector, entertainment industries, and tourism (Sugathan and Ranjan, 2019; Coudounaris and Sthapit, 2017). Customer experience remains a topic of high interest and importance for both managers and academics (Keiningham et al., 2020) due to its importance at a personal, organizational, and societal level.

Experiences are at the very core of the tourism industry. They embrace an integral part of the travel, tourism, event, and hospitality sector. They are regarded as generators of memories (Coudounaris and Sthapit, 2017). "Remembered" experiences are acknowledged as a dominant force in consumers' future choice behaviour. A strong sensorimotor association with a past service experience may lead consumers to think more frequently about their experience and ultimately lead to improved word-of-mouth recommendations (Reitsamer et al., 2020). In addition, experiences may trigger positive emotional responses, consecutively contributing towards value creation for individuals. For instance, tourists gaining and benefiting the most from their time/money/effort spent at a particular tourism organization or setting. It has been advocated that a human being implicated as a person in a focal interactive system is a value creator (Ramaswamy and Ozcan, 2018; Grönroos and Voima, 2013). Indeed, consumers may shape and create their own value from their experience. Service providers may also foster the value of a tourist experience by providing "exceptional" service or offering increased opportunities for socializing and relationship building. Despite such "human-related" aspects, other factors such as the place itself and technological advancement may shape tourists' experiences. As a result, tourists may potentially perceive experiences as valuable, life-changing, unexpected, astonishing, surprisingly good and satisfying (Christou, 2020a; Huang et al., 2016). Besides this, tourists rely on cognitive and emotional involvements/transactions in the physical or artificial world (such as the case of virtual reality) to feed their travel cosmology and form perceptions of the (tourism) world. This may eventually be translated into guest dis/satisfaction and future behavioural intentions, such as positive/negative word-of-mouth recommendations, re-visits and loyalty (Christou, 2020b). It has been advocated that technological advancement may impede or enhance the tourist experience (Fusté-Forné, 2021; Han et al., 2019). Currently, intelligent automation is enforced by tourism organizations to improve procedures for customers and impact favourably on their overall experience. One such type of intelligent automation that has received increased attention by the research community is the use of robots. Certain researchers argue that future tourism will take place in a type of "robonomic" experiential environment in which the vast majority of tourists will enjoy a highly automated tourist experience (Webster and Ivanov, 2019). This increased academic attention may possibly turn on the fact that robots are creators of intense reactions for their users, as well as contributors to the overall experience of consumers (Fusté-Forné, 2021). As Park (2020, p. 10) appropriately positions, "one of the vital purposes to adopt service robots is to enhance consumer experiences".

Various studies have examined the "demand", that is, consumer side, in terms of perceptions and reactions in response to intelligent automation. These have yielded some important outcomes regarding the perceptions of people in relation to the endorsement of (e.g.) robots in businesses and the impact of these on their experiences. Study findings on such perceptions vary, with some being positive, such as the generation of positive emotions. For instance, the study of Kuo et al. (2017) identified that both "curiosity" and "fun" aroused in consumers. Even so, most studies refer to contrasting results by noting both positive and negative perceptions of people that lead to either enhanced or deteriorated experiences. In the study of Fusté-Forné (2021), within the context of gastronomy tourism, robot chefs were perceived as creators of unique entertainment experiences. However, the same study also revealed that such robots are "feared" for their potential to dehumanize dining.

Another study that investigated attitudes toward robot concierges revealed that guests preferred caricatured robots in terms of shape and appearance. Yet, even those who expressed favourable attitudes towards robot concierges also expressed a preference for human employees over robots. Their reasoning was based on the fact that human-human (compared to robot-human) interactions are sincere and genuine (Shin and Jeong, 2020). Similarly, users in the study of Tung and Au (2018) felt insecure and "freaked out" when they had to share the same physical environment with robots. These feelings were particularly more intense in tightly spaced areas, such as elevators.

Negative emotional responses from people in response to robots in tourism are based on various reasons. These may include personal reasons, such as the reluctance of some people to interact with robots. Also, the manner in which some robots resemble/act as humans may ultimately trigger feelings of awkwardness and eeriness. Furthermore, there is concern about possible malfunctions of automated procedures and robots, as well as the inability of machines to respond to specific needs or provide personalized service. All these factors may result in feelings of frustration and disappointment. Finally, people may express fears that technological and robot determinism will take over and replace humane, genuine, authentic, and sincere interactions between tourists and service providers (Christou et al., 2020; Fuentes-Moraleda et al., 2020; Bhimasta and Kuo, 2019; Tung and Au, 2018). Even so, human-resembling robots have started being used in the service sector. This, despite arguments that anthropomorphism may increase feelings of discomfort for consumers and pose a threat to their human identity (Mende et al., 2019). The relationship between anthropomorphism and customer use is complex with research results once more being mixed (Blut et al., 2021). This is why researchers (such as Park, 2020) call for further research regarding this complex topic.

It may be argued regarding to what extent intelligent automation may replace human assistance and perhaps most importantly "caregiving" towards people with special needs, people with disabilities, elders, and minors. The role of human-provided assistance/service is vital in such cases. Tourism organizations, including airlines and hotels, often provide special, personalized, and human assistance to people with special needs in order to relieve anxiety feelings, and causing guests to feel welcomed, comforted, safe, and "being taken care of". One such example is Singapore Airlines (2021), which states the following on its official site:

For the visually-*impaired, our cabin crew will conduct a special safety briefing before take-off and help orientate them to their surroundings. Our cabin crew will also assist in preparations for meal consumption and help identify food items.*

Tourism organizations may be nominated and awarded by official bodies based on the soft and hard skills of their employees and the "personal service" they provide to passengers in their attempt to enhance their on-board experiences (Skytrax, 2019). Nonetheless, in commenting on the COVID-19 pandemic, Coombs (2020) made reference to a key argument in favour of increased artificial intelligence adaptation, which includes peoples' preferences having changed in favour of a degree of intelligent automation and an increased familiarity with such technologies. In all likelihood, the application of IA in tourism is expected to increase in the future, while according to some researchers (such as, Tussyadiah, 2020) there is a need for further studies to prepare the sector for a more automated future. Likewise, Lu et al. (2020) feel that there is a need for more empirical research within the general sphere of IA, particularly in the case of service robots and their impacts on behaviour, well-being, and the potential downsides for service customers. Besides this, in the case of negative experiences resulting from the implementation of IA, tourism organizations run the risk of being negatively commented on in social networks and having their image damaged. This poses a dilemma to service organizations within the tourism sector regarding the extent to which they are to embrace IA, particularly in the form of robotics. On one hand, robotic devices could be associated with better organizational performance (Ballestar et al., 2020) and opportunities for "interesting" interactions with customers. On the other hand, as discussed earlier, they may trigger undesirable emotional responses and negative future intentions.

Technological advancement, innovation, digitalization, and smart procedures penetrate business functions, societies, cities and businesses within (Bresciani et al., 2021; Popkova et al., 2021; Ferraris et al., 2018; Ferraris et al., 2017). All the same, a number of studies in the tourism and general business field highlight the importance and value of new technology for organizations that want to obtain greater performance and deliver value co-creation (Allal-Chérif et al., 2021; Lalicic and Weismayer, 2021; Bresciani et al., 2018). Yet, answers to the questions of how, when, and where businesses and their managers should use automation technologies remain rather elusive, hence this topic deserves further attention by the academic community (Engel et al., 2022; Zarkadakis et al., 2016).

3. Methodology

3.1. Research purpose, design, and context

Based on the aforementioned discussion and research gap, the purpose of this study is to explore the extent to which intelligent automation should be used to provide the best possible customer service quality and experience to customers from a service-provider angle. The *supply side* is an important perspective that has been rather overlooked by researchers in the academic community. Qualitative inquiry principles have been employed to enable deep understandings of people's (in this case, suppliers) perceptions, opinions, and feelings in the topic under investigation (Christou and Farmaki, 2019). Our study draws on an inductive qualitative inquiry which is consistent with the exploratory nature of the study and well suited to answering "how" questions (Yin, 2018). Hence, it provides an in-depth exploration (Christou, Hadjielias, & Farmaki, 2019a; Farmaki et al., 2020) and a better understanding of a scarcely researched topic with no clear theoretical basis (Rodell, Sabey, & Rogers, 2020). The study focuses on tourism providers in Cyprus, and more specifically, tourism agencies, tour operators, guided tour services, and tourism accommodation establishments. Cyprus was regarded as an ideal place context as it is particularly popular for the international tourist clientele, with tourism contributing significantly to the country's economy (Zopiatis et al., 2020). The tourism sector of this European country is well established, and uses several tourism services that address various age groups and differing types of visitors, being supported by technologically-advanced services and infrastructure (Christou, 2018).

3.2. Sampling and data collection

In line with previous work researching the use of innovative technologies within a tourism context (Hadjielias, Christofi, Christou, & Drotarova, 2021; Stylos et al., 2021), we carried out qualitative in-depth interviews with managers from respective tourism organizations. Managers are key informants within tourism organizations who can elaborate on the strategic decisions of their firm, including decisions to adopt intelligent automation (Hadjielias, Christofi, Christou, & Drotarova, 2021). To identify suitable informants and achieve the study's objectives, we employed a combination of purposive and snowball sampling strategies (Bazi, Filieri, & Gorton, 2020; Husemann, Eckhardt, Grohs, & Saceanu, 2016).

First, based on the principles of purposive sampling, which is a type of non-probability sampling (Jahanmir, Silva, Gomes, & Gonçalves, 2020) interviewee selection was based on a number of (inclusion) criteria (Bosangit & Demangeot, 2016). A key selection criterion was to choose managers who had knowledge on intelligent automation and who could influence firm decisions regarding the adoption of intelligent technologies (Hadjielias, Christofi, Christou, & Drotarova, 2021). Another important criterion was to select a diverse sample of research informants for obtaining insights on the research phenomenon from multiple perspectives. Based on this criterion, the selection of informants took into consideration their background, role, position within their company, age, and gender, to ensure that proper diversity could be found within the sample (Farmaki et al., 2020).

Second, drawing on snowball sampling, research informants fitting the above criteria were recruited through contacts of the co-authors and recommendations from interviewees (Hussain, Salia, & Karim, 2018). The end sample (see Table 1) includes informants who are (professional) managers or owner-managers from diverse companies operating within the tourism sector. These include tour operators, tour guided services, travel agents, hotels, short-term rental management companies, theme parks, online booking platforms, and destination management companies.

In line with other inductive studies examining technology adoption in the tourism sector (Liu & Hung, 2021; Spencer, Buhalis, & Moital, 2012), we used in-depth semi structured interviews to collect data from our sample. In-depth interviews are well-suited to obtaining rich and meaningful information (Ferraris et al., 2019a), such as from tourism providers (Hadjielias, Christofi, Christou, & Drotarova, 2021). The questions in the interview protocol were primarily focused on identifying the perceptions and attitudes of tourism providers against intelligent technologies, and their understandings of how intelligent automation can be used to provide the best possible customer service quality and experience. However, the research informants were also provided sufficient space to speak freely about other related matters in the course of the interview (Spencer et al., 2012). The interview protocol employed open-ended questions in order to gain deep insights on respondents' perceptions, attitudes, and opinions (Ferraris et al., 2019a; Spencer et al., 2012) on intelligent automation. Open-ended questions were included under broader interview themes (McAdam, Harrison & Leitch, 2019) and included*: (1) Background information about the company and research respondent; (2) Experiences and use of intelligent automation at work; (3) Perceptions and attitudes towards intelligent automation?; (4) Benefits and costs/drawbacks from using intelligent automation?; (5) Aspects of the tourism experience that can be enhanced with the application of intelligent automation?,* and (6) *human-intelligent automation interaction.*

Prior to commencing our study, we carried out a pilot study with three informants: one general manager of a travel agency, one owner-manager of a guided tours company, and one owner-manager of an accommodation booking platform. In line with previous work, the pilot interviews were not included in the final sample and were primarily used for refining and improving our study's interview protocol, with the intention of making the interview questions more understandable to the research participants (Hadjielias, Christofi, Tarba, 2021; Hadjielias, Dada, Eliades, 2021). Before each interview, the purpose of the study was communicated to the research participants. These were informed that their participation was strictly voluntary and that they could either refuse to participate or they could withdraw at any time during the interview (Bonfanti, Vigolo, & Yfantidou, 2021). Participants were guaranteed full anonymity and confidentiality of their responses (Burghausen & Balmer, 2014).

Each interview lasted, on average, between 45 and 55 min, and these interviews were audio recorded (Essamri, McKechnie, & Winklhofer, 2019). Complementary notes on nonverbal aspects were taken by the

Table 1
Profiles of Participating Firms and Respondents.

N.	Type of enterprise	Size - # employees	Year of establishment	Respondent code	Respondent Role
1	Guided tours	7	2002	R1	Co-founder
2	Tour operator	51	1996	R2	General Manager
3	Travel agent	18	1988	R3	General Manager
4	Hotel (4 star)	78	1983	R4	General Manager
5	Online Booking Platform	12	2010	R5	Owner
6	Travel agent	25	2007	R6	Co-founder
7	Guided tours	11	2012	R7	Co-founder
8	Hotel (4 star)	105	1991	R8	General Manager
9	Hotel (5 star)	142	1994	R9	General Manager
10	Boutique Hotel	15	2009	R10	Founder
11	Restaurant	9	2000	R11	Owner
12	Airport operator	301	2005	R12	Operations Manager
13	Guided tours	14	1999	R13	Founder
14	Online Booking Platform	8	2008	R14	Co-founder
15	Airline Company	144	2015	R15	General Manager
16	Short-term rental property management company	32	2014	R16	General Manager
17	Travel agent	17	2004	R17	Founder
18	Boutique Hotel	35	2014	R18	Founder
19	Transportation Company	23	1985	R19	Owner
20	Hotel (5 star)	162	2001	R20	General Manager
21	Hotel (3 star)	31	2006	R21	Founder
22	Tour Operator	38	1997	R22	General Manager
23	Destination Management Company	16	2011	R23	Co-founder
24	Hotel (4 star)	79	2001	R24	General Manager
25	Boutique Hotel	11	2015	R25	Founder
26	Travel agent	28	1995	R26	General Manager
27	Hotel (3 star)	37	2004	R27	General Manager
28	Travel Agent	16	2008	R28	Co-founder
29	Tour Operator	47	1997	R29	Tour Manager
30	Hotel (5 star)	205	1972	R30	Food and Beverage Manager
31	Theme Park	52	1999	R31	Owner
32	Hotel (5 star)	154	1993	R32	Front Office Manager
33	Travel Agent	13	1993	R33	Owner
34	Hotel (4 star)	83	1989	R34	General Manager
35	Short-term rental property management company	21	2015	R35	General Manager
36	Guided tours	8	2015	R36	Founder
37	Hotel (3 star)	32	1999	R37	General Manager
38	Short-term rental property management company	28	2016	R38	General Manager
39	Hotel (4 star)	89	1991	R39	Front Office Manager

researcher during the interview process, as suggested by qualitative researchers (Christou et al., 2018). Semi-structured interviews were carried out, allowing the collection of individual respondent meanings in the form of ideas, opinions, and emotions, while encompassing a common structure to aid the subsequent comparison of data between interviews (Autio et al., 2011; Hadjielias, Christofi, Vrontis, & Khan, 2022).

The interviews were carried out between February and April 2021 at the organizational premises of each research participant (Morrish & Jones, 2020). In line with previous work, the interviews were carried out in the native language (that is, Greek), of the research participants (Hadjielias, Christofi, & Tarba, 2021). Drawing on an inductive research process, data were collected and analyzed based on an iterative process until reaching saturation; the point where new theoretical insights can no longer be gained with additional data collection (Hampel, Tracey, & Weber, 2020; Chase & Murtha, 2019). The saturation point was reached when collecting data from our 39th research informant. Consequently, the findings of 39 interviews with owners or managers of tourism-related businesses were retained in the study, and were used in data analysis.

3.3. Data analysis

Following previous practice, the interviews were initially transcribed verbatim in the Greek language and subsequently transcribed into the English language (Grinevich et al., 2019) using a back-translation process (Harbi, Thursfield, & Bright, 2017). The interview transcripts were 22–25 double-spaced pages in length on average, with a total number of 895 pages from the 39 interviews.

While analysing our data, the Gioia methodology was applied (Gioia, Corley, & Hamilton, 2013) which involves three distinct analytical stages. During the first stage of the analysis, an inductive open coding process was facilitated which involved scrutiny of the interviews line by line, transcript by transcript, to code chunks of text such as sentences, phrases, and words (Corbin & Strauss, 2014; Holton, 2007) while adhering to participant terms (Gioia et al., 2013). The first analytical stage led to the generation of a large number of emergent "first-order concepts", which were included in a master coding list (Hadjielias, Christofi, & Tarba, 2022).

During the second stage of analysis, an axial coding process was facilitated (Corbin & Strauss, 2014). This involved looking at the list of "first-order concepts" produced during the first analytical stage to group them into fewer "second-order categories" based on the similarities between them (Corbin & Strauss, 2014; Holton, 2007). During the second stage, the process of analyzing the data shifted to abductive in order to provide comparisons of the emergent themes with the literature. This enabled us to gain a better understanding of the findings and to identify which of these findings reflected existing concepts and which reflected new notions (Dubois & Gadde, 2002; Sillince et al., 2012). This back-and-forth process between the analyzed data and the literature helped us to get a better sense of interrelationships between our emergent concepts and categories, allowing us to distil second-order categories into fewer aggregate dimensions during our third and last analytical stage (Gioia et al., 2013). Fig. 1 provides the data structure of our -findings, illustrating the relationships between first-order concepts, second-order categories, and aggregate dimensions.

4. Findings

4.1. Perceptions of tourism providers of IA: Ascertaining the value-addedness and applicability of IA in tourism

Industry professionals use a number of IA techniques widely, and they perceive them as factors that add value to their internal and external customers, as well as to their organization. Interviewee R4 discussed IA techniques and how they are being used by their organization, by identifying firstly the importance of those techniques (referring to the functionality/efficiency aspect), and secondly, the "demand" arising from customers: *"Can we actually perform our everyday duties and keep our customers happy without using IA techniques? Even the older*

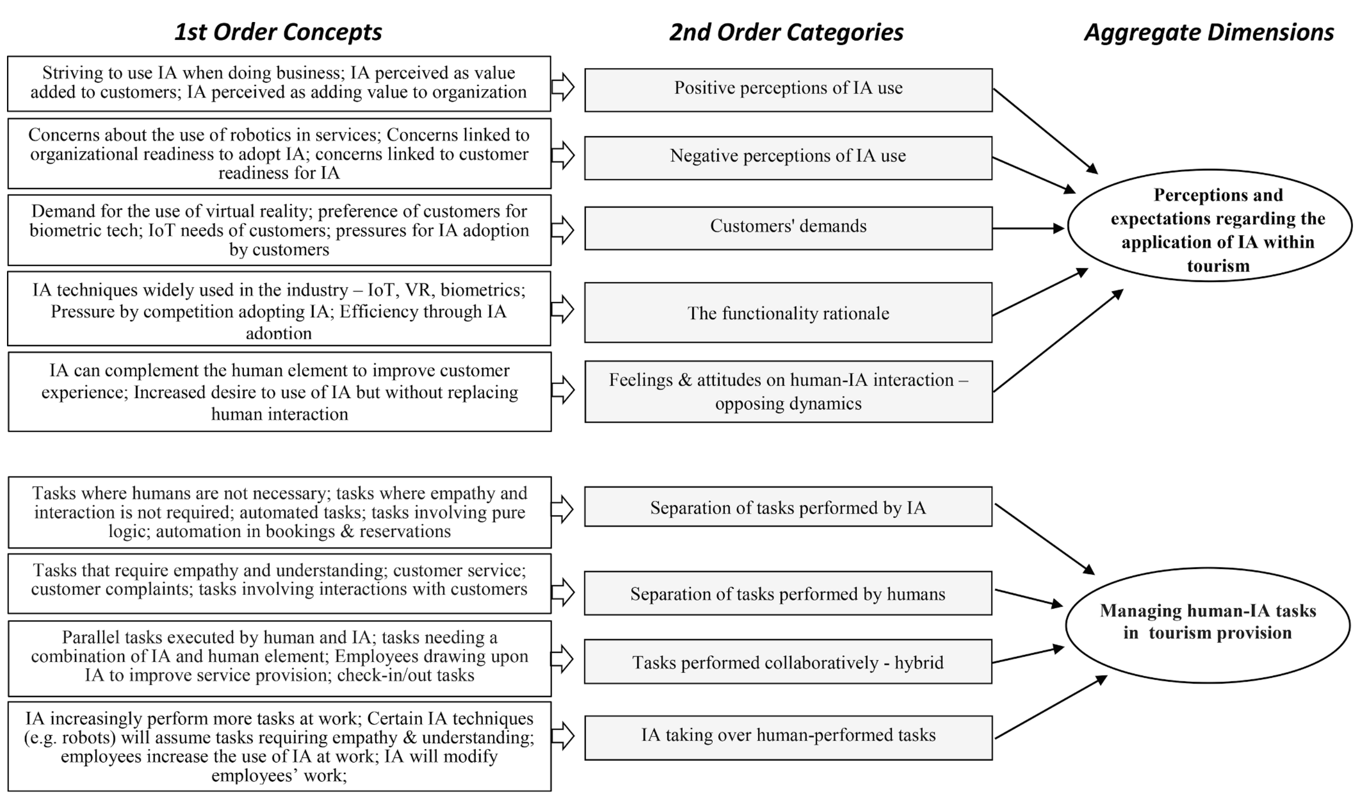

Fig. 1. Data structure.

customers are expecting them nowadays, and this puts pressure on us to increase the use of technology even more.".

Various technological advancements seem to be preferred more by industry professionals. The most highly preferred are the internet of things, biometrics, and virtual reality. There is a general perception that these three advancements are highly preferred by customers (demand-led dynamics). Interviewee R7 fully supported the great benefit of the use of virtual reality: *"Through the virtual tour, we provide tourists with a realistic point of view, whether they live nearby or somewhere else in the world. That's really fascinating, and I am very happy that we are able to do that. Customers love it as well."* Hence, the functionality rationale and the demand/pressure of customers is brought up by the *supply end.* Research has so far indicated that the use of IA techniques will be increasing in the future and this seems to be the reality for organizations that will be struggling if they do not manage to add this value for their customers (Tussyadiah, 2020; Mende et al., 2019; Atzori et al., 2017).

On the other hand, informants stressed the cost factor often associated with the use of IA as a prohibiting factor. They also expressed increased hesitation and concern with the use of specific forms of IA, such as the case of robots in the service context. Their hesitation reflects to some extent some personal (i.e., negative) perceptions regarding the use of certain IA technologies. For instance, R9 expressed concerns about the increased use of robotics in the industry: *"I know some do use them, even direct competitors. As a management team, we have been trained and we know a lot about their existence and how they can be utilized. We do not use any kind of robotics now, but I know that at some point in the future it will be inevitable. I am not sure if all customers will be ready for it."* Likewise, R22 said the following: *"I am not a fan of all these technological advances that are actually eliminating the use of the human factor to the minimum required, but this is today's reality. If you do not manage to advance your organization and what it offers in terms of all those advances, then you are left with customers that will be dissatisfied in that aspect. And I am not talking about the younger generations only."* Industry professionals are sceptical about the increased use of a number of IA techniques (such as, robotics) and this is evidenced both in this current research as well as in the literature (Baisch et al., 2017; Broadbent et al., 2008; Huang and Rust, 2018; Mende et al., 2019). Fig. 2 below summarizes in a diagrammatical format the use and provision of IA, as informed and shaped by tourism providers' perceptions in regard to IA in service provision, customers' demand for IA services, and functionality rationale (e.g., the availability of supporting technology to provide specific IA-linked services).

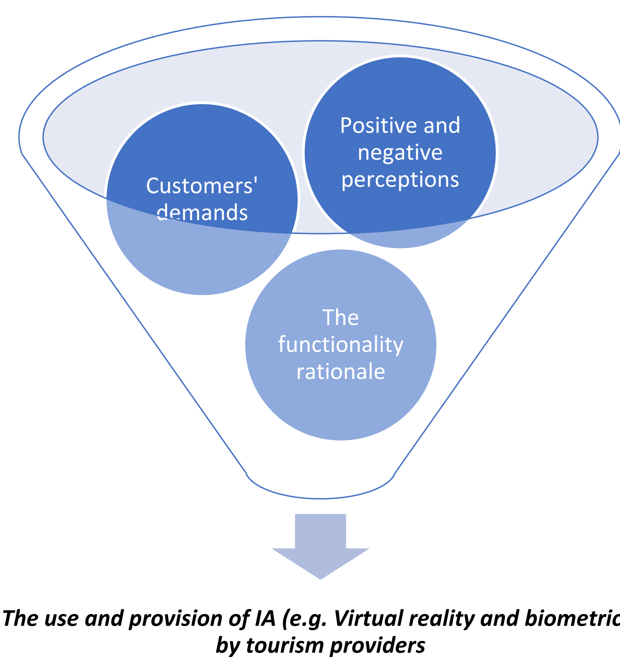

Fig. 2. Filters for the use and provision of IA as expressed by tourism providers.

4.2. Perceptions on human-IA interaction: The tourism provider perspective

Perceptions vary in regard to how tourism providers feel about the increased use of IA in the current tourism scene. Issues of willingness to use them due to the increased needs of customers more or less contradict the element of losing the "human touch" that is present in the participants' responses. R12 said: *"For airports contending with increasing passenger numbers, expanding the use of advanced technology should help in terms of airports' ability to handle enhanced capacity and operational flexibility. This is the future's reality. On the other hand, I believe we are losing the interaction between people, and this seems a bit disturbing to me.".*

The human element seems to be still very important to tourism providers, but they support the tendency to use IA as long as this does not interfere with the human interaction. Some level of human element is desired by them, such as interviewee R15, who stressed: *"The increased need to use IA improves passenger experience as the process becomes much more seamless, which helps drive revenue generation for airline companies. This will involve airlines investing in those technologies in the short term, but there are indeed long-term effects. I would not eliminate the human interaction completely, though; this would not reach the fully desirable outcomes that service provision requires".* Parallel views are expressed by interviewee R32: *"If I was told that I need to interact with a non-human element and that this required no human interaction at all it would make me feel uncomfortable, especially when their appearance is inconsistently humanlike. It would make me feel much more uncomfortable if there was no real human interaction at all and it was all up to the IA techniques…".*

Based on the above, there seems to be an understanding and a support of the use of IA, as long as it does not eliminate human-customer interaction. The feeling of potential discomfort from human-robot interaction and the need to interact to a certain extent with customers seems to be fully supported by tourism providers. This outcome addresses critical questions set in the literature as to the future of IA in tourism (Tussyadiah, 2020), as discussed in the theoretical section of this paper. Fig. 3, which follows, summarizes the contradictory views and attitudes of informants regarding the use of IA. In more detail, there seems to be opposing dynamics linked to IA provision, with certain contradictory feelings being expressed by informants. The diagram illustrates the willingness of service providers to support the use of IA to address increased customer demands, as well as to *"improve passenger experience"* (R15) and not to eliminate the human factor, particularly within the service provision context.

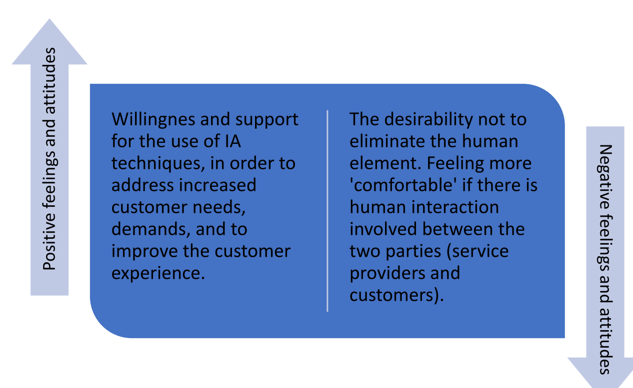

Fig. 3. The opposing dynamics linked to IA provision as expressed by tourism providers.

4.3. Task allocation and cooperation between humans and IA in tourism: Separating the boundaries

There seems to be a clear distinction between the service providers in terms of how they envision IA and people "cooperating" effectively towards providing the best possible customer service experience. To a large extent there is a separation of tasks that IA and people undertake at the moment, but it seems that industry professionals perceive this as the beginning of a new era in tourism. On one hand, there was a clear distinction in responses between tasks that require empathy and understanding and dealing with dissatisfied customers (e.g., providing personalized and enhanced customer service, and handling customer dissatisfaction). On the other hand, there seems to be a very positive attitude towards IA technology in procedures in which the human element is not necessary, such as the case of bookings/reservations. A rather "grey zone" probably remains in the case of check-in/out tasks, which may be performed by either means, or in combination of IA and employees. Shifting completely to IA (in service provision) is not preferred, and the responses are negative in regard to this aspect. Interviewee R20 was very clear: *"I can clearly see the need to use more IA techniques and even robotics, which is the future. But, I cannot see a robot treating a dissatisfied customer. It would be so wrong. I don't want this interaction to be completely machine-led – it is simply not desired."* In agreement with the previous response, interviewee R39 added: *"I am working 30 years in this industry, and I must say that human interaction cannot be stopped completely. I don't know what the future is, but for sure we still need people for certain tasks. Customer satisfaction depends on how humane I am and how polite. A smile on my face is always helpful. Can we get robots that genuinely smile? I am afraid they will do that in the future but right now we are simply not ready for that. Customers neither."*.

According to the opinions of informants, technology will slowly overtake humans in terms of performing more tasks in the workplace. Interviewee R28 said: *"I know that the future holds a lot. I believe more tasks will be overtaken by machines and robots. There are things that technology cannot do, such as empathizing with the customer. They could do that in the future, though, but now we need both to survive."* Even so, based on providers' responses, there is a clear distinction as to what tasks can be completely overtaken by IA and those that should remain in "human hands". However, it is perceived by interviewees that in the future more tasks will be allocated to technology, with both positive as well as negative outcomes. According to R22: *"With the increasing use of technologies, employees will have to use them to complete daily tasks. Then their minds will not grow and stick with the daily routine. Employees will not get a challenge in their work, and their talent will not grow. Also, they might feel trouble in having face-to-face communication, because for face-to-face contact, you need different communication skills."* It is perceived that the increased use of technology will modify the way people perform their work, as well as the way people feel and react to certain job requirements. This supports previous evidence from the literature – that increasing the use of technology results in various consequences, towards customers and employees (Cohen and Garcia, 2008; Cornil and Chandon, 2013; Curtis, 2016). Fig. 4, which is presented in the form of a Venn diagram, illustrates the current overlapping tasks between IA and human-performed tasks, and how technology penetrates those task areas that have traditionally been offered by employees.

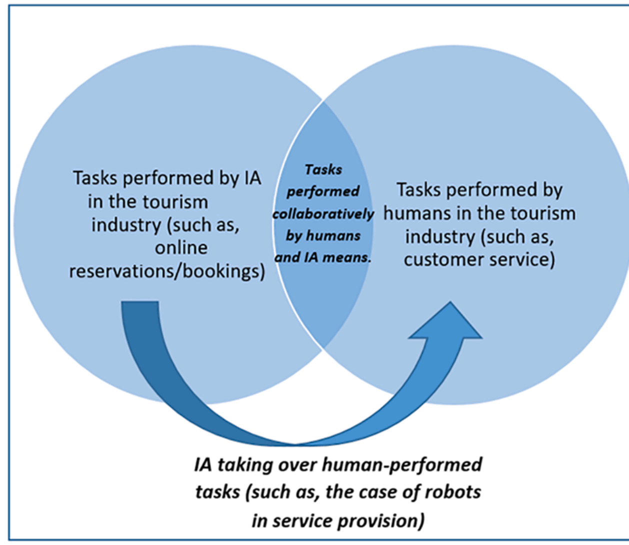

Fig. 4. IA taking over human-performed tasks.

5. Discussion

5.1. The value and usage of IA in the industry, and a reply in regard to which aspects of tourism service and experience can be enhanced with the application of IA

A very important component of this study is the fact that it provides perspectives from the *supply end* in regard to IA and how it will be utilized by service providers in the future. Through the current study several outcomes have been revealed as to the value of IA within the service context, and more specifically in the tourism industry. Through the findings of this study, it may be acknowledged that there is a highly perceived value among industry professionals regarding the use of IA. In more detail, the outcomes of the study have revealed that the use of IA is perceived as a way to increase both value and efficiency in a number of ways. Firstly, IA assists organizations to perform activities much faster and in a more effective way than in the past. Secondly, tourism providers recognize that IA enhances customers' experiential value and, consequently, increases their satisfaction. Thirdly, service providers are fully aware that customers are expecting – and in all likelihood demanding – IA to be used by them.

Nonetheless, informants acknowledge the significant role of human–human (compared to human-IA means) interactions in securing "sincere" and "genuine" (Shin and Jeong, 2020) experiential provision for their customers. In more detail, aspects of the tourist experience that can be enhanced with the application of IA are (and should remain) restricted to functional and rather arithmetic/computerized elements, such as the case of booking arrangements, the internet of things, and biometrics. Practitioners recognize that IA offers solutions to problems and provides effective means for them in dealing with large numbers of customers simultaneously, as well as implementing procedures in a fast, efficient, and error-free manner. As a result, this enables them to respond more appropriately to customer demands and requests, while adding customer experiential value. Furthermore, they recognize that some areas of experiential provision are enhanced through the use of IA. These findings are in accord with findings linked to IA in its most advanced form. Specifically, in the case of virtual reality and/or interactive technology which enables providers to contribute towards value and experiential creation (Kirova, 2021; Flavián et al., 2019).

Literature so far has researched whether customers are willing to accept automations in customer service procedures and the extent to which it offers value to them (Baisch et al., 2017). Our findings have shown that industry professionals are experiencing positive comments regarding the use of IA in service provision – not only by the younger generation, but also by the older generation. The latter age group may not be comfortable in using all IA-linked provided means, but in general, they seem to be willing to accept them. As a result, this brings us to the conclusion that the use of IA in service provision may offer great value to the industry. Hence, professionals are urged to use it since they may harvest positive results in terms of offering customer value and satisfaction. Nonetheless, a probable obstacle for implementing certain IA technologies is the cost factor, as explained by providers. Also, for those aspects of the service provision/experience that require a more emotional and empathetic engagement by the two parties, then the human factor is not only deemed extremely important, but vital. This is despite the fact that a number of organizations in recent times have proceeded with the employment of automated means to reply to customer complaints. All the same, fears that technological determinism (such as in the form of robots) are taking over and replacing human, genuine, authentic, and sincere interactions between service providers and customers is once more highlighted, as in previous studies (Christou et al., 2020; Fuentes-Moraleda et al., 2020; Bhimasta and Kuo, 2019; Tung and Au, 2018). Of great importance is the acknowledgement of the *supply side* – that human–human interactions are extremely important within the service provision context and should remain “in human hands”.

5.2. The degree of automation as opposed to the human element, and a reply in regard to how should humans and IA separate and/or merge their tasks to improve tourism service and experiential provision

The level of acceptable automation, as opposed to the human element, has been an interesting finding of this study. It has been argued that as part of the urgent need to respond to the pandemic, organizations looked to the application of IA (Coombs, 2020). This, largely to the extent of the human element being almost or even completely excluded from the delivery process (Cuthbertson, 2020). As expressed by the informants of this study, there is a clear and acceptable degree of fully utilizing technology for certain tasks instead of using the human element (such as, for reservations). It has been acknowledged in the current literature that the level of automation is an element that needs to be addressed and discussed by future researchers (Mende et al., 2019; Tussyadiah, 2020). This study has made a step towards addressing this issue. More specifically, service providers through their responses, support on the one hand the full utilization of IA techniques for certain mechanic tasks, such as booking/reservation arrangements and reporting special requests. A grey zone probably remains in the case of check-in/check-out tasks which can be performed either by humans or automated means, or as a combination of both means. On the other hand, it has been strongly stressed by the participants that the human element should remain a vital component during service provider/customer interactions, particularly in the case of a more personalized level of service.

This finding seems promising for the future of the tourism industry, which is strongly founded upon anthropocentric, loving and caring, hospitable and welcoming pillars (Christou and Sharpley, 2019; Christou et al., 2019; Lashley, 2015). Yet, the informants do not fail to express “fears” (in this case coming from the supply side) that IA will continue to take over traditional human-performed activities in the service context. Fig. 5 illustrates IA and human overlapping relationships, as discussed above and in the previous section. More specifically, the stacked Venn diagram with its circles highlights the use of IA for functional and experiential purposes in the service context (such as the case of “virtual reality”), while being supported by the human factor. The hybrid (IA and human) offering assumes an optimum use of technology that does not reject or ignore the human factor in shaping experiences and creating customer value. This hybrid offering addresses customer demands for new technology in service provision, while simultaneously assuaging their concerns about technology taking over (Christou et al., 2020). While technology may increasingly penetrate into human territory, such as in the case of robots replacing traditional human tasks in service provision, it is important to safeguard the human element and its core (for the tourism industry) characteristics. These characteristics embrace actions of politeness, a genuine smile, empathy, and hospitality offering that may not be replaced by robotic or other technological and automated means.

5.3. Theoretical contributions

There are three main theoretical contributions that arise from this study. First, by researching the *supply side* (that is, tourism organizations) perspective on IA, this study addresses recent calls to understand how and where businesses and their managers should use automation technologies (Engel et al., 2022; Zarkadakis et al., 2016). We provide new theoretical understanding on the perceived value-addedness and applicability of IA in organizations including the dynamics and overlap of IA and the human factor in service provision. Our study contributes to the acknowledgement of a significant dimension/factor (that of the human element and its individual characteristics) within the overall penetration of IA technologies and digital transformation of businesses in the contemporary world (Verhoef et al., 2021).

Second, this study addresses a gap regarding the use of IA in the service delivery process. It provides insights regarding the use of IA

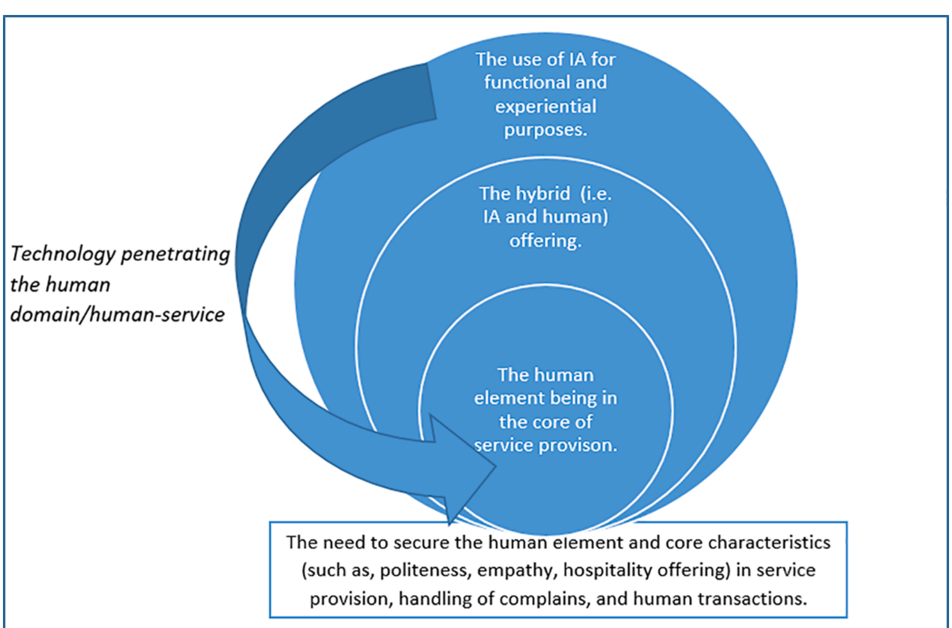

Fig. 5. The overlapping IA and human relationship in service provision.

within service organizations, that are characterized by certain idiosyncrasies that involve both automated and human means in the service delivery process (Akdim et al., 2021; Christou et al., 2020). This study acknowledges the pivotal role of IA in forming, shaping, and even enhancing tourism service experiences. Even so, it progresses by adding the crucial element of the "human factor" and its personal characteristics expressed in the service context when it comes to the adoption of IA within service provision. Such as for instance, the significant role and impact of a genuine smile, hospitality provision, and empathetic stance on behalf of service providers.

Third, this study contributes to the discourse of human and associated human characteristics/capabilities in a highly technologically advanced and digitally transformative industry. As has been discussed in this paper, there is a need to identify both the value that IA offers to a service-linked industry, as well as the degree of automation in comparison with the human element. The current study has revealed that there is a tremendous value in regard to utilizing IA techniques effectively and efficiently. Even so, this does not imply the exclusion of the human factor in the context of service provision and experiential value for our customers. Although the current situation of COVID-19 and measures linked to physical (human) distancing have led to the further embracement of IA in the tourism industry (Cuthbertson, 2020), this study stresses the human factor in service provision. Also, in an era in which technology has penetrated the tourism industry (Fusté-Forné, 2021; Park et al., 2021; Cha 2020), it is vital to safeguard the human factor, especially in the case of service/experiential provision. This does not imply the rejection of technological means and digital transformation that may be used to enhance the overall tourist experience, but instead the supplementing of these with one of the strongest (in its traditional sense) pillars of the tourism industry – that is, the human factor and its hospitality-related individual characteristics.

5.4. Practical implications

Current research has provided insights on the perspectives of customers regarding the use of IA, interactive technology, and new technology in the service provision context (Kirova, 2021). This study complements such findings, with outcomes delivered from the supply service-provision side. We are able to offer certain suggestions that are mainly directed towards service providers.

The tourism industry may benefit from the current research in a number of ways. First, it is suggested that practitioners and managers make use of IA techniques for their benefit, without however marginalizing the human factor (and its individual characteristics) when it comes to service provision. That is, a heavy reliance on technological means for service provision purposes may reduce – from both parties involved (that is, service providers and customers) – opportunities for personal communication and fruitful human–human interactions. Human relations, emotional exchanges, and hospitable service characterize the tourism domain (Solnet et al., 2019; Christou and Sharpley, 2019), and it seems that it shall continue to fuel the industry, despite challenges, digital transformation, and technological advancement. Second, it is recommended that practitioners use IA primarily for functional purposes and for enhancing the experiential value for their customers (such as, the case of robots, virtual reality tours and online experiences). Nonetheless, such IA means are to be complemented by the human element, particularly in case there is a problem that cannot be resolved through technological means. For instance, having an actual human person dealing with dissatisfied customers rather than an automated system may result in a more immediate, sincere, and personal manner of addressing customers' concerns and issues.

Third, practitioners could actively and continuously seek the opinion of their clientele in regard to which specific services are to be performed by IA or/and humans. As presented in this study, some duties fall under certain/clear categories, such as the case of online reservations. Yet in other cases, the boundaries between the use of IA and human provision remain rather blurred and in grey areas, such as the case of a receptionist that may be replaced by a touch screen. Probably, a hybrid-offering that offers the opportunity for both technology and human interaction may work better in this case.

5.5. Limitations and future research opportunities

Despite the useful outcomes that were derived from this study, there are certain limitations that ought to be acknowledged. First, this study has not consulted the demand side (that is, customers). Though this may come across as a major limitation, it is stressed that there are several current studies that have examined tourists' perceptions and views regarding the use of IA in the tourism domain. Future studies may be directed to explore IA within services from both supply and demand ends, which can help to comprehensively and simultaneously capture the aspects of service provision that can be enhanced through IA and/or humans. Future qualitative studies drawing on nested case study research (Thomas, 2011) could focus on cases of specific service industries, researching sub-units at both the supply (e.g. service organizations, suppliers, industry experts) and demand-side (i.e. customers) to obtain comprehensive empirical insights (Pershina et al., 2019) about IA adoption within services.

Second, this research has not taken into consideration specific tasks or practices within service organizations that can be fully automated, but adopted a general approach and left this open to be discussed by the research participants. Future studies could embark on in-depth exploration leading to typologies classifying tasks between these that can be fully adopted by IA, others that are reliant on the human element, and those that can be undertaken by hybrid approaches. At the same time, future qualitative studies could produce typologies of respondents displaying different clusters of managerial attributes, attitudes, and behaviours regarding the adoption of IA within services. Such typologies will help in getting a better grasp of the task and managerial-specific dynamics that govern the effective adoption of intelligent technologies within service organizations.

Third, due to the fact that our study was carried out within a specific place context, hence elicited insights from managers of a homogeneous cultural background, this may limit the generalizability of our results to other country-contexts and organizations managed by people with different cultural backgrounds. Future qualitative and quantitative studies could further investigate IA usage and customers' reactions while focusing on cultural elements and the perspectives of people coming from various cultural backgrounds (Ferraris et al., 2019b). Future research can also compare the findings of this study with other studies that may draw results from service suppliers coming from differing cultural backgrounds, and others coming from economies that may be heavily reliant upon technological means to perform tasks.

Fourth, while the study focuses on managerial perceptions, it interviews informants at one time point (i.e. cross-sectional). Yet, available evidence highlights that managers' perceptions change over time (Maule & Hodgkinson, 2003) through accumulated experiences or due to changes in the external business environment (Dowell & Killaly, 2009). As a result, a cross-sectional study like ours cannot sufficiently capture the antecedent conditions forming managerial perceptions (Sousa, Lengler, & Martínez-López, 2014) on IA, neither the way these perceptions change over time. Future research producing longitudinal data can be useful to examine changes in managers' perceptions of IA. In this way, studies could provide additional insights into the causal relationships and other dynamics involved in the formation of managers' perceptions regarding IA. Longitudinal studies could also be useful in terms of mapping the sequence of changes in managerial perceptions over specific critical events (e.g. crises or transformations in the external environment).

6. Conclusion

The main purpose of this study was to explore the extent to which intelligent automation (IA) should be used to provide the best possible customer service quality and experience. This study has addressed concerns in regard to the level of automation to be used within the service context (Tussyadiah, 2020; Mende et al., 2019). More specifically, it has taken into account suppliers' perspectives in regard to intelligent automation in tourism. The perspectives of tourism suppliers have been rather overlooked in previous studies, despite the fact that these suppliers come into direct contact with customers, are receivers of their requests, comments, reviews, and feedback, respond to their demands, and they are the key people responsible for shaping experiences for customers.

The study has employed qualitative inquiry principles to enable deep understandings of people's (i.e., suppliers) perceptions and opinions (Christou and Farmaki, 2019). The findings were derived from the interviews of 39 managers or owners of tourism-linked businesses, and were analysed through the Gioia methodology (Gioia et al., 2013) which involved three distinct analytical stages. The analysis of findings enabled further understandings of those aspects of the tourism experience that may be enhanced with the application of IA, and addressed issues concerning which tasks are to be performed by humans to improve service/experiential provision, as expressed by service tourism providers. Of note is the importance of the human element and associated individual characteristics and key capabilities (e.g., a welcoming/warm attitude) that are not only to be not ignored, but rather reenforced in a highly digitally transformative and increasingly automated service industry, such as the tourism field.

As a concluding statement, this study stresses the importance of IA in the current and in all likelihood future tourism scene, yet simultaneously highlights the significant role of the human element within the service delivery context, despite external challenges such as the COVID-19 pandemic and the technological advancement that is pervading the entire tourism industry.

CRediT authorship contribution statement

Prokopis Christou: Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Elias Hadjielias:** Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Aspasia Simillidou:** Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Olga Kvasova:** Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization.

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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