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# AI and robotics in the European restaurant sector: Assessing potentials for process innovation in a high-contact service industry

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## Abstract

The restaurant technology market is rapidly evolving and is transforming the restaurant business as a significant sector of tourism and hospitality. Enabled by artificial intelligence (AI), mobile apps, kiosks and chatbots revolutionize the guest experience and robots automate restaurant operations. Despite the increasing interest, the use of AI and robotics in restaurants is still in its early stage and restaurant managers are seeking guidance to leverage these technologies for service excellence. In this high-contact service sector, emotional skills need to be balanced with the possible automation potentials. The present research analyzes the current state of AI and robotics in the restaurant sector and proposes a systematic identification of process innovation potentials. For this purpose, a market analysis of the European AI and robotics market for restaurant operations is conducted, which yields a first knowledge base for future research and conceptual work. Besides detailed empirical data, a reference process is developed for leveraging new technologies for process innovation.

**JEL classification** L86 · O14

**Keywords** Artificial intelligence · Robotics · Restaurant industry · Restaurant technology · Smart tourism

## Introduction

The restaurant technology market is rapidly evolving and transforms the restaurant business as a significant sector of tourism and hospitality. Enabled by artificial intelligence (AI), mobile apps, kiosks and chatbots profoundly change the guest experience (Hospitality Tech 2018; Tussyadiah and Park 2018) and robots independently automate restaurant operations, e.g. Ivanov et al. 2019; Ivanov and Webster 2019. AI and robotics are perceived as key value drivers (Berezina

et al. 2019; Ivanov et al. 2017; Mintel 2020; Oracle 2019) and experts expect the rise of these technologies to result in a wide-ranging disruption of traditional service operations and to inherit a large potential for process innovation (Bock et al. 2020; Davenport 1993; Ferreira et al. 2020). Similar to other sectors, this will transform the service industry due to effects of labor automation, productivity growth and new forms of networked service interactions between organizations, employees, and their customers (Chui et al. 2016; World Economic Forum 2018). However, the knowledge on AI and robotics is still considered low in organizations (Pumplun et al. 2019; Ransbotham et al. 2017). In particular, the technologies for restaurant operations represent a rather novel phenomenon (Berezina et al. 2019; Mathath and Fernando 2015). Companies still have difficulties in creating business value from the technological potentials of AI and robotics (Alsheibani et al. 2020; Dietzmann and Alt 2020; Hofmann et al. 2020). Moreover, restaurant managers are confronted with the question of how to manage the shift of manual tasks from service employees to technological systems, especially in times of staff shortage and growing concerns of job replacements (CUF 2018; World Economic Forum 2018). In the traditional people-driven business, they

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need to decide how human and artificial intelligence can work together “as a team” to create new forms of customer experiences and networked business interactions in restaurant ecosystems (Genysis 2017; Paluch and Wirtz 2020; Berezina et al. 2019).

In addition to the automation potential in the restaurant industry (Chui et al. 2016; CUF 2018), the service sector is also characterized by a high level of customer contact. High-contact service sectors usually require social and emotional skills to achieve excellence in hospitality, customer satisfaction and loyalty on the customer side (Prentice 2014; Prentice et al. 2020; Qiu et al. 2020). Thus, restaurateurs must be aware of the capabilities of AI and robotics technologies in substituting this human work and need to carefully decide how to deploy innovative technologies in their daily business processes. As restaurant businesses often lack any organizational IT structure (Cavusoglu 2019; Moreno and Tejada 2019), restaurant operators require specific advice on identifying opportunities and redesigning processes.

Service literature demands interdisciplinary research and conceptual knowledge that help service operators to determine the suitable technology for their purposes while considering the future collaboration between human and artificial intelligence (Paluch and Wirtz 2020; Rafaeli et al. 2017; Wirtz et al. 2018). Despite the increasing academic interest in AI and robotics in the restaurant business (Berezina et al. 2019; Ivanov et al. 2019; Mathath and Fernando 2015), a systematic assessment of opportunities for process innovation is missing in current academic literature. The research field is characterized by single case studies or experiments in lab settings, but lacks empirical data to establish conceptual knowledge as the foundation for decision support (Ivanov et al. 2019; Lu et al. 2020).

This paper aims to close this gap with a systematic view of AI and robotics technology providers that offer concrete service solutions to restaurateurs. Following the call for more research on service technologies (Kunz et al. 2019; Wirtz et al. 2018), it systematizes current service solutions using AI and robotics technologies and contributes to the understanding of the opportunities for process innovation in the restaurant sector. It enriches current research on AI and robots in service operations, which is still in its infancy and requires knowledge on how technologies impact business practices and human work (Ferreira et al. 2020; Kunz et al. 2019). Furthermore, the paper seeks to evaluate the progress of existing AI and robotics service solutions in performing human tasks. Even if research demonstrates the potential of AI and robotics for all human tasks in service operations (Frey and Osborne 2017; Huang et al. 2019), a quantitative view on existing technologies is missing to fully understand their capabilities, specifically in a high-contact service sector. This applies to the European restaurant sector where an empirical analysis of the European AI and robotics vendors shall offer

insights to accumulate knowledge for conceptual work from a practical perspective.

For this purpose, two research questions are suggested:

**RQ 1:** Which opportunities for process innovation are offered by current AI and robotics service solutions in the European restaurant sector?

**RQ2:** How advanced are current AI and robotics service solutions in performing human tasks in restaurants’ business operations?

The paper is structured as follows: The foundation part provides related research and describes the potential of AI and robotics in service processes. It also contains an overview of relevant research in the restaurant sector. After describing the methodology in section 3, the fourth section describes key results of the empirical analysis. Finally, a reference process is proposed to guide future decision processes of service managers. A detailed discussion and existing research restrictions concludes the paper.

## Theoretical foundations

### Process innovation and artificial intelligence

A business process is defined as “a set of logically related tasks performed to achieve a defined business outcome” (Davenport and Short 1990, p.4). Following previous research in this field, process innovation may be described as a new, efficiency-enhancing activity intended to reduce the cost of producing a good or a service (Davenport 1993; Trantopoulos et al. 2017; Un and Asakawa 2015). Process innovation may occur with any existing technology and is recognized as a key differentiator nowadays (Vom Brocke et al. 2016). To achieve process innovation in organizations, (digital) technologies are incorporated into existing business processes to increase efficiency and to remain competitive (Davenport 1993; Vom Brocke et al. 2016). However, technological functionalities must not be simply incorporated into existing business processes. Instead, these processes should be redesigned to successfully integrate novel technologies into business operations. Hence, business process and business network redesign require a high degree of business transformation and highly depend on organizational factors (Alt 2006). In this respect, employees and decision-makers need to learn how to apply novel technologies and to adopt new work routines (Damanpour and Gopalakrishnan 2001; Venkatraman 1994; Vom Brocke et al. 2016).

AI and robotics are increasingly important in enabling process automation and innovation in organizations (Bughin et al. 2018; Hull et al. 2015; Willcocks et al. 2015; Zebec 2019). In general, the AI-discipline engineers and deploys AI-enabled computing systems (Kaplan 2016; Simon 1995) to create machine intelligence that mimics human intelligence. Making

machines “intelligent” requires certain abilities, such as reasoning, problem-solving, learning, communicating, perceiving, and acting (Huang and Rust 2018; Russell and Norvig 2016). Literature in this field often focuses on specific methods or techniques, such as machine learning and reinforcement learning or targets specific technologies, such as decision support systems, data mining, or big data (Nascimento et al. 2018). One promising field is the development of robots. Service robots can be described as “system-based autonomous and adaptable interfaces that interact, communicate, and deliver service to an organization’s customers” (Wirtz et al. 2018, p.909). They were explored either in the form of virtual service robots (i.e. chatbots, digital assistants) or physical robots (Murphy et al. 2019; Paluch and Wirtz 2020; Wirtz et al. 2018). With the rise of big data, sensors and interconnected cyberspaces, AI applications have reached a new level: By permanently analyzing data, extracting knowledge and deducting tasks, AI technologies no longer only simulate human intelligence. Instead, the focus is on creating hybrid intelligence by combining machines and humans in networked processes (Kaplan and Haenlein 2019; Pan 2016).

When tapping into the field of AI and robotics, the identification and prioritization of opportunities in business areas is a key issue for creating process innovation (Davenport 1993; Harrington 1999; Davenport and Ronanki 2018). Use cases for business success must be identified (Davenport and Ronanki 2018) and process characteristics, e.g. knowledge intensity or required creativity, need to be considered (Davenport 2015; Seidel et al. 2015). Consequently, service organizations require a detailed understanding of how to approach new opportunities for process innovation and which technologies can perform certain tasks in their business processes (Davenport and Ronanki 2018).

### AI and robots in restaurant processes

Although the application of technology in the hospitality and tourism sector is not new (Buhalis and Law 2008; Gretzel et al. 2015), the use of AI and robotics in restaurant operations represents a rather recent phenomenon (Berezina et al. 2019; Mathath and Fernando 2015). In view of the changing restaurant market, businesses have started to experiment with AI technologies and robots (Hospitality Tech 2018). Similarly, a growing interest can be observed in academic research (Berezina et al. 2019; Cain et al. 2019; Ivanov et al. 2019; Maier and Edwards 2020; Yang et al. 2020). In particular, the restaurant business has received attention from multiple research disciplines and offers promising research opportunities (Ivanov et al. 2019; Rosete et al. 2020). The adoption of AI and robotics service solutions offers a range of possibilities for process innovation in this industry (Ivanov, and Webster, C. (Eds.). 2019) and can lead to productivity growth, or improvements in customer service processes (Berezina et al. 2019;

Gretzel 2011; Ivanov et al. 2017). Especially service robots have been the subject of many articles (Murphy et al. 2019; Paluch and Wirtz 2020; Wirtz et al. 2018).

With the focus on current opportunities for process innovation, the present research screened existing literature in the Ebsco and Springer databases. Using the keywords “restaurants, artificial intelligence and robots” a narrative literature review was conducted (Rhoades 2011) to investigate possible applications of AI and robots in restaurant processes. Ivanov et al. (2019) and Ivanov and Webster (2019) provide a general overview of the applicability and effects of AI and robotics technologies in business processes. Berezina et al. (2019) also explore widely the deployment of AI and robotics and present diverse use cases for restaurants. Similarly, Cain et al. (2019) as well as Maier and Edwards (2020) describe the automation potential of AI and robotics and how this impacts business processes and the design of future service systems. As shown in Table 1, the application of AI and robotics in academic research ranges from data-driven table planning to sales forecasting or the development of diverse robots. Industry reports present additional applications, such as location planning, menu planning, or dynamic preparation times (Oracle 2019; Hospitality Tech 2018). In the following, only application scenarios for restaurateurs were included and solutions aimed at consumers, e.g. recommendation engines for restaurants, were not regarded in the analysis.

In sum, academic literature is often descriptive and consists mainly of case studies or prototype developments (Ivanov et al. 2019). Scholars develop scenarios for the tourism of the future or use restaurant data for their research, e.g. sentiment analysis of customer reviews. At the same time, detailed empirical data is missing due to generally low adoption rates in practice (Ivanov et al. 2019; Cain et al. 2019). Furthermore, Ivanov et al. (2019) observe a strong emphasis in the literature on the use of robots in hospitality while the potential of algorithm-based applications is often ignored or considered secondary. Finally, most application scenarios discussed by researchers take place in the US or Asia (Ivanov et al. 2017; Ivanov, and Webster, C. (Eds.). 2019; Yang et al. 2020). AI and robot applications in the European market are less in the focus or are even ignored in the (scientific) discussion. Accordingly, the examination of the European technology market of AI and robotics vendors offers novel empirical insights to develop a systematic view of current opportunities for process innovation, which may serve as a knowledge base for practitioners and researchers.

### Automation potential

AI and robotics are becoming increasingly significant in service industries and are transforming traditional processes (Huang and Rust 2018; Paluch et al. 2020; Wirtz et al.

**Table 1** Research in the restaurant sector focusing on AI and robotics

Business processes	
Customer operations	<ul style="list-style-type: none"> <li>• Service robots and robotic waiter systems (Acosta et al. 2006; Berezina et al. 2019; Claveau and Force 2019; Eksiri and Kimura 2015; Mathath and Fernando 2015; Qing-xiao et al. 2010; Tzou and Kuo 2009; Yu et al. 2012)</li> <li>• Object detection on images for automated checkout systems (Aguilar et al. 2018; Ziller et al. 2019)</li> <li>• Operation scheduling (Nonaka et al. 2018)</li> <li>• Delivery robots (Wang et al. 2017)</li> <li>• Chatbots and voice-activated technologies that enable ordering, payment or customer information, e.g. Domino Pizzas DOM (Berezina et al. 2019)</li> <li>• Biometric identification, i.e. facial recognition integrated in self-service technologies: ordering, payment, preference management (Berezina et al. 2019; Morosan 2011; Wu and Cheng 2018)</li> </ul>
Reservation	<ul style="list-style-type: none"> <li>• Chatbots for reservation retrieval (Berezina et al. 2019)</li> <li>• Data-driven table planning (Tan and Staats 2020; Vidotto et al. 2007)</li> </ul>
Marketing	<ul style="list-style-type: none"> <li>• The analysis of marketing campaign effectiveness based on logistic regression modelling (Chen 2019; Liu et al. 2001)</li> <li>• Automated marketing promotion via chatbots, voice assistants, and kiosks (Ivanov 2019)</li> <li>• Customer segmentation (Sarvari et al. 2016)</li> </ul>
Reputation management	<ul style="list-style-type: none"> <li>• Reputation management (Claypo and Jaiyen 2014; Kaviya et al. 2017)</li> <li>• Sentiment analyses of restaurant reviews (Beck and Libert 2017; Gan et al. 2017; Kim and Song 2013; Kouvaris et al. 2018; Krishna et al. 2019; M. Govindarajan 2014)</li> </ul>
Human resource management	<ul style="list-style-type: none"> <li>• Recruitment processes (Sato et al. 2019)</li> <li>• Shift scheduling method using planning algorithms by considering human and robot tasks (Prentice et al. 2020; Tanizaki et al. 2017)</li> <li>• Automatic labor planning in quick service restaurants (Noone and Coulter 2012)</li> <li>• Time tracking using biometrics (Berezina et al. 2019)</li> </ul>
Food and beverage preparation	<ul style="list-style-type: none"> <li>• Analysis and development of recipes using neural networks based on recipe data of combined ingredient lists, cooking instructions and food images (Herranz et al. 2018; Marin et al. 2019; Salvador et al. 2017)</li> <li>• Liquid handling control for service robots (Komoguchi et al. 2008)</li> <li>• Cooking robots (Berezina et al. 2019; Yan et al. 2007)</li> <li>• Beverage management (alcoholic and non-alcoholic) (Gonzalez et al. 2019)</li> <li>• Kitchen Operation (Mathath and Fernando 2015)</li> </ul>
Supply chain management	<ul style="list-style-type: none"> <li>• Smart fridges at restaurants for automated food ordering (Ivanov 2019)</li> <li>• Improved inventory management and planning using time series analyses (Leon-Garcia et al. 2016; Liu et al. 2001)</li> </ul>
Management: business and finance	<ul style="list-style-type: none"> <li>• Sales forecasting (Lasek et al. 2016; Xinliang and Dandan 2017) and revenue management (Noone and Maier 2015)</li> <li>• Demand prediction and production planning in quick service restaurants (Noone and Coulter 2012)</li> <li>• Demand forecasting in restaurants (Tanizaki et al. 2019)</li> </ul>

2018). On the one hand, service literature predicts that the rise of technologies will result in a massive shift of work tasks from human workers to AI-enabled technologies (Chui et al. 2016; Bughin et al. 2018; World Economic Forum 2018). Promising opportunities for human-robot collaboration, or the augmentation of service employees are discussed (Huang et al. 2019; Huang and Rust 2018; Larivière et al. 2017; van

Doorn et al. 2017). On the other hand, AI and robotics also enable a high degree of service automation and threatens traditional service jobs (Huang and Rust 2018; Larivière et al. 2017; McClure 2018). Specifically, in the food and accommodation industry, studies estimate that 75 to 85% of work activities could be augmented or replaced by AI and robotics (Chui et al. 2016; CUF 2018).

However, the abilities of AI and robots in performing human tasks varies depending on the specific task and the required skills for mastering the activities of this task. The potential of AI technologies should not be assessed by looking at the occupation level. Instead, the activity or task level determines whether human tasks may be replaced by AI and robotics or whether technology should rather enhance human work (Chui et al. 2015; Huang and Rust 2018; Larivière et al. 2017). Usually, jobs are characterized by a range of simple and more complex tasks (Chui et al. 2015; Huang and Rust 2018). For example, Huang and Rust (2018) describe, that specific tasks require certain levels of human intelligence, i.e. mechanical, analytical, or more emotional or intuitive intelligences. Similarly, Wirtz et al. (2018) distinguish between cognitive, analytical, or social emotional work.

Generally, researchers agree that tasks with a more repetitive, homogeneous, and structured character are easier to automate through AI and robotics (Davenport 2017; Frey and Osborne 2017; Lu et al. 2020). This mechanical work is often routine, non-creative and unskilled labor without any required education or knowledge (Chui et al. 2015; Huang and Rust 2018; Wirtz et al. 2018). Chui et al. (2016) assume that a strong share of activities in foodservice businesses are susceptible to automation by AI due to a predictable character of most activities. In the current hospitality literature, AI and robotics technologies primarily substitute functional and repetitive tasks that lack intellectual and socio-emotional capabilities (Ivanov et al. 2019; Rosete et al. 2020). Yet, AI or automated agents have shown their ability to substitute even non-routine and more complex activities (Brynjolfsson and McAfee 2011; Frey and Osborne 2017; Huang et al. 2019). In data- and information-intensive processes, tasks may easily be supported by AI since machines have the advantage of processing a large amount of data. Some authors even believe that algorithm-based machine learning and data analytics will soon surpass humans in the decision-making of analytical tasks (Huang and Rust 2018; Paluch et al. 2020; Wirtz et al. 2018). The literature review equally identified a range of application scenarios for analytical tasks supported by AI, e.g. demand forecasting or shift scheduling (cf. Table 1).

On the contrary, human tasks are not yet affected in the same way if they require more empathetic and intuitive skills (Huang and Rust 2018; van Doorn et al. 2017; Wirtz et al. 2018). This stream of research recognizes that service robots fail to have the capability to feel and show emotions towards customers even in the near future. Robots are able to imitate human behaviors or emotional expressions (Bartneck et al. 2009; Wirtz et al. 2018) or can create a form of social presence (Belanche et al. 2020; van Doorn et al. 2017). Nonetheless, they are not yet able to develop emotional-social capabilities or authentic emotions (Paluch et al. 2020; Wirtz et al. 2018). At the same time, hospitality literature (Rosete et al. 2020; Qiu et al. 2020; Prentice 2014; Prentice et al. 2020) states that

these emotional-social capabilities are particularly important in service organizations with a high level of direct customer contact (Bardzil and Slaski 2003; Walker 2017). Hospitality strongly depends on these emotional skills, such as creativity or emotional support, as employees need to manage interpersonal interactions with customers and must perform “emotional labor” to create positive customer experiences (Prentice et al. 2020; Rosete et al. 2020). Frontline service employees as “stewards of customer contact and relationship management” (Garry and Harwood 2019) require a particularly high level of such emotional intelligence (Garry and Harwood 2019; de Keyser et al. 2019). They not only create emotions on the customer side that affect perceptions of service quality and satisfaction (Rafaeli et al. 2017; Singh et al. 2017). Frontline service employees also compromise negative emotions in the service delivery process (Groth et al. 2019; Rafaeli et al. 2017).

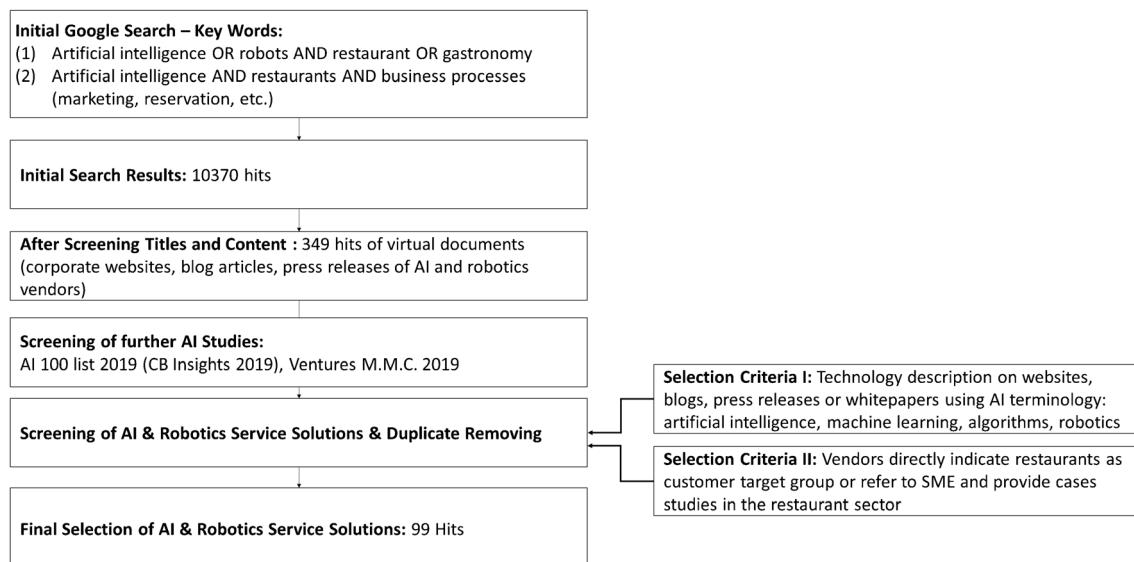
After collecting detailed experiences with robots, hospitality firms in China even removed their service robots and are rethinking their strategy on how to use AI-based technology (Gale and Mochizuki 2019; Qiu et al. 2020). They fear that service robots erode the positive hospitality experience (Beldona and Kher 2015; Gursoy et al. 2019). Recent research proposes therefore that the ability to deliver emotional, hedonic and utilitarian aspects will be critical for robots to be successfully integrated into the service delivery process (Lu et al. 2020; Rosete et al. 2020). For this reason, academic literature emphasizes the need for future research that focuses on the deployment of AI and intelligent robots adopting emotional work in the hospitality sector (Ivanov et al. 2019; Lu et al. 2020).

## Research methodology

The following section provides an overview of the methodology and presents the data collection and data coding process. Current AI and robotics service solutions in the European restaurant market are analyzed that take advantage of AI and robotics technologies. The goal is to obtain insights in the current state of AI and robotics service solutions in taking over human tasks and to structure current opportunities for process innovation.

## Data collection

The data sample consists of the five biggest food service markets in Europe: France, the UK, Italy, Spain and Germany (including Austria and Switzerland) (Statista 2017). The data collection took place in a multi-step approach that is presented in Fig. 1. First, a search engine approach via Google identified the results of relevant documents. For this purpose, several keywords in the respective languages were applied, i.e.



**Fig. 1** Selection process of relevant AI and robotics service solutions

artificial intelligence, robots, restaurant, gastronomy and the relevant business processes (e.g. marketing, supply chain management, reservation, etc.). After screening title and content of first results, 349 hits of corporate websites, press releases or blogs were selected that described AI and robotics service solutions in those five markets. The first selection criterion was derived from specific AI terminology, such as machine learning, robotics, algorithms, etc. As a second selection criterion, only vendors were included that specifically targeted restaurant businesses as a customer segment. Finally, studies, such as the AI 100 list 2019 (CB Insights 2020) or MMC Ventures 2019, were sighted to find additional vendors that are active in the restaurant sector. After removing duplicates, our final sample consists of 99 AI and robotics service solutions.

## Data coding

The analysis emphasized four dimensions to build first classifications. This follows prior work, which has demonstrated that the classification of service technologies can assist in building an initial knowledge base, specifically in immature service application fields (Allmendinger and Lombreglia 2005; Hunke et al. 2020; Remane et al. 2016). Therefore, systematizations may serve as a foundation for future conceptual frameworks in underdeveloped research areas (Remane et al. 2016; Hambrick 1984; Nickerson et al. 2013). In a first step, coding dimensions for a provisional coding approach were defined (Bryman 2012; Saldaña 2009) and existing conceptual work was used for this purpose (Huang et al. 2019; Kreutzer and Sirrenberg 2020; Larivière et al. 2017; Russell and Norvig 2016; Wirtz et al. 2018). Pre-established categories guided the analysis similarly to a taxonomic coding approach (Saldaña 2009) and dimensions as

well as possible values for each dimension served as a codebook during the analysis. They were documented in a coding scheme along with guiding principles to be considered in the coding process (Bryman 2012). The conceptual dimensions (1) business processes and subprocesses in the restaurant sector, (2) application fields of AI capabilities (Kreutzer and Sirrenberg 2020), (3) intelligence level of tasks (Huang and Rust 2018; Huang et al. 2019) and finally (4) the role of technologies in service processes (Larivière et al. 2017; Marinova et al. 2017) are presented in the following paragraphs.

## Business processes and subprocesses in the restaurant sector

In the following, the business process description by Ivanov (2019) was used and relevant subprocesses were complemented following Ivanov and Webster (2019), and Moreno and Tejada (2019). This breakdown of processes was also discussed with an industry expert. These business processes and sub-processes (see Table 2) were then used to scan the sample for processes covered by AI and robotics vendors.

## Application fields of AI capabilities

Following the AI literature (e.g. Russell and Norvig 2016), AI solutions should feature at least the following skills of intelligent systems: (1) natural language processing (NLP), (2.) knowledge representation, (3) automatic reasoning to identify patterns, (4) machine learning to learn from its own activities and new circumstances, (5) computer vision in the form of image analysis and processing and (6) robotics to move or manipulate objects. Nowadays, AI solutions often combine these skills in intelligent agents, service robots or digital

**Table 2** Business processes and subprocesses in the restaurant sector

Business Processes	Corresponding subprocesses
Customer operations	Customer information, customer service incl. complain management, order taking, consulting/selling, serving, payment, online delivery management, capacity and queue management
Reservation	Reservation retrieval, table yield management
Marketing	Segmentation, campaign and promotion planning, design, campaign execution (across channels, e.g. Social Media, email, etc.), and menu design
Reputation management	Review management (search and reply)
Human resource management	Recruiting, staff planning and scheduling, staff training and development, incident management
Food and beverage preparation	Recipe creation and menu planning, cooking and drinks, kitchen device management
Supply chain management	Procurement planning, distributor price negotiation, order/procurement management incl. administration, inventory management incl. planning, controlling and food waste management, quality, hygiene and food security control
Management: business and finance	Business strategy, forecasting and budget planning, accounting, controlling and reporting

assistants (Russell and Norvig 2016; Wirtz et al. 2018). Especially, machine learning, automatic reasoning and knowledge representation are widely applied. Following the categorization for AI application fields of Kreutzer and Sirrenberg (2020), four application fields using these AI capabilities were defined: (1) Natural language processing (NLP), (2) computer vision, (3) robotics, and (4) expert systems. Robotics is understood in this research as the physical ability to move objects following the definition of Russell and Norvig (2016). Expert systems represent algorithm-based programs (Buchanan 1986) offering promising solutions for decision making as well as process automation and contain components for knowledge building, problem solving and communicating solutions based on machine learning (Cortez et al. 2018; Turban and Watkins 1986).

### Intelligence level

As mentioned in section 2.3., different intelligence skills are necessary for diverse tasks. According to the theory of AI job replacement (Huang and Rust 2018), four intelligences exist in the context of service tasks: mechanical, analytical, intuitive, and empathetic intelligences. In their subsequent work, Huang et al. (2019) mainly distinguished between mechanical, thinking and feeling or emotional intelligences in a refined definition. Following this framework, the third dimension is used to assess the intelligence level of business processes and corresponding subprocesses. For this purpose, this research orientated on Huang et al. (2019) that analyzed the intelligence level of service tasks and used the O\*NET database with about 1000 job and task descriptions to assign 41 tasks (i.e.

“monitor processes, materials, or surroundings” or “thinking creatively”) to the three intelligence levels. Based on these task descriptions, the tasks were assigned to the subprocesses to determine their specific intelligence level (see Table 3 and the Appendix for all subprocesses). The intelligence level of each subprocess was reviewed and challenged with a restaurant manager with more than ten years of experience to increase the validity of each assignment. This led to a total of five main intelligence levels: (1) mechanical, (2) mechanical and thinking, (3) thinking, (4) thinking and emotional and finally (5) primarily emotional subprocesses. Some subprocesses, such as *human resource management: staff planning*, contain diverse activities from administrative to inter-relational tasks and as a consequence require intelligences on all three levels. In these cases, the majority of tasks with a specific intelligence level defined the corresponding intelligence level of the subprocess. During the analysis, the service solution was assigned to the level of intelligence of the subprocess it supports.

### Role of technology in service processes (Augmentation vs. Replacement)

Service literature describes the different role of technology in augmenting or substituting service employees (Larivière et al. 2017; Marinova et al. 2017; de Keyser et al. 2019). Technology that augments service employees assists and complements the work of humans during the service encounter and in back-of-house processes (Larivière et al. 2017; Marinova et al. 2017). If technology substitutes human work, service employees are no longer involved in the task execution



**Table 3** Assignment of tasks to corresponding subprocess and resulting intelligence level

Business process: human resource management		
Subprocess	Tasks	Level of intelligence
Recruiting	Getting information (me), scheduling work and activities/ performing administrative activities (me), processing information (th), interpreting the meaning of information for others (th), judging the qualities of things, services or people (th), making decisions and solving problems (th), communicating with persons outside the organization (em), staffing organizational units (em)	Thinking (Th)
Staff planning and scheduling	Getting information (me), scheduling work and activities (me), performing administrative activities (me), estimating the quantifiable characteristics of products, events or information (th), organizing, planning and prioritizing work (th), updating and using relevant knowledge (th), coordinating the work and activities of others (em), communicating with supervisors, peers or subordinates (em)	Mechanical (Me) and thinking (Th)
Staff training and development	Coaching and developing others (em), training and teaching others (em), development and building teams (em), establishing and maintaining interpersonal relationships (em), processing information (th), judging the qualities of things, services or people (th), provide consultation and advice to other (th), communicating with supervisors, peers or subordinates (em), guiding, directing and motivating subordinates (em), staffing organizational units (em)	Thinking (Th) and emotional (Em)

(Larivière et al. 2017). The fourth analysis dimension was examined to improve the understanding on how subprocesses are currently empowered by AI and robotics solutions and how vendors position the role of service solutions in association to service employees (augmentation vs. substitution).

The data set consisted of virtual documents in the form of textual descriptions of enterprise websites of AI and robotics vendors, blog articles, press releases or technical descriptions of AI and robotics vendors. This data was coded and analyzed by one author in total. In order to classify the respective AI and robotics service solutions, several coding rules were defined to minimize the effects of interpretations and to achieve consistency during the analysis phase (e.g. Bryman 2012). As shown in Fig. 2, AI capabilities were assigned by screening relevant keywords in available documents, e.g. conversational AI, automatic speech, or voice recognition for the category *NLP*. Similarly, relevant business processes and subprocesses that vendors described in the presentation of their solutions were checked to understand how they position their technology in association to service employees. To ensure the validity of the coding process, a set of 10% was additionally validated by an AI expert in an ex-post quality check. For this sample, an intercoder agreement of 98,6% as percentage agreement and a Cohens Kappa (Cohen 1960) of 92,5% were achieved. According to Landis and Koch (1977) this represents a strong agreement among coders which indicates the quality level of the coding process.

## Analysis results

The market analysis of AI and robotics service solutions identified 99 service solutions in the European restaurant market. Technologies include AI software and robotics solutions that are offered to restaurant operators. Solutions designed for consumers were not considered (e.g. for restaurant search). Moreover, the analysis did not distinguish between different restaurant segments. This is in line with the call of DiPietro (2017) to broaden the perspective beyond restaurant segments to reach more comprehensive results for the sector. A descriptive data analysis process was chosen as follows by counting the respective AI and robotics service solutions that correspond to the analysis dimensions.

## Opportunities for process innovation

Similar to the academic literature, empirical data provides insights into the manifold opportunities for process innovation by AI and robots. Moreover, several patterns were identified of how AI and robotics solutions are currently being utilized for business processes in the restaurant sector. Vendors have developed promising solutions that often provide support for multiple processes. Back-of-house processes are specifically in the focus of technology vendors: More than half of them ( $n = 69$ ) offer solutions for back-of-house processes. At the same time, vendors also strive to optimize the service encounter: About 55 applications aim to increase efficiency in front-of-house processes. The majority of service

<p><b>Business Processes/Subprocesses</b></p> <ul style="list-style-type: none"> <li>• <b>Values see table 1</b></li> <li>• Coding based on the descriptions in virtual documents by screening relevant business processes and subprocesses</li> <li>• Multiple coding was possible as vendors often support more than one process</li> </ul>	<p><b>AI Capabilities</b></p> <ul style="list-style-type: none"> <li>• <b>Values:</b> NLP, computer vision, robotics, expert systems</li> <li>• Coding based on the descriptions in virtual documents by screening the following <b>key words</b> <ul style="list-style-type: none"> <li>• <b>NLP:</b> e.g. <i>conversational AI, language/speech/conversation-based + AI or machine learning, speech/voice recognition</i></li> <li>• <b>Computer Vision:</b> e.g. <i>automated vision, object detection, product or meal detection, OCR in combination with machine learning, image analysis/recognition</i></li> <li>• <b>Expert Systems:</b> e.g. <i>intelligent algorithms, machine learning, self-learning systems, AI-based software</i></li> <li>• <b>Robotics:</b> physical robots</li> </ul> </li> <li>• Multiple coding was possible</li> </ul>	<p><b>Intelligence Level</b></p> <ul style="list-style-type: none"> <li>• <b>Values:</b> mechanical, thinking, emotional intelligence</li> <li>• Coding based on the associated intelligence level of the subprocess that is addressed by the vendor</li> <li>• The level of the subprocess was identified by the assignment of tasks on different intelligence levels using the classification of Huang et al. 2019 – see Appendix</li> </ul>	<p><b>Role of technology</b></p> <ul style="list-style-type: none"> <li>• <b>Values:</b> augmentation, substitution</li> <li>• Coding based on descriptions in virtual documents by screening the following keywords <ul style="list-style-type: none"> <li>• <b>Augmentation:</b> e.g. <i>assistance, employee support, enhancement of employees' work, improved decision making</i></li> <li>• <b>Substitution:</b> e.g. <i>self-service, fully-automated, autonomous, fully technology provided</i></li> </ul> </li> </ul>
<p><b>Data Sources</b></p> <ul style="list-style-type: none"> <li>• <b>Virtual Documents:</b> Websites, blog articles, press releases of AI and robotics vendors, if available technical descriptions</li> </ul>			

**Fig. 2** Coding dimensions, classification rules and data sources within the coding process

solutions ( $n = 84$ ) are related to the processes *customer operations, management: business and finance, human resource management* and *food and beverage preparation* (see Table 4).

By analyzing the application fields of AI capabilities (NLP, computer vision, robotics, expert systems), it becomes evident that certain capabilities and functionalities are applied more frequently in certain business processes (see Table 5): Expert systems are prominently used by AI and robotics vendors: 35 identified solutions primarily take advantage of algorithm-based machine learning in the form of expert systems. Specifically, in back-of-house processes AI service solutions are present as expert systems in *human resource management* or *business and finance operations*. Here, analytical tasks of the sector are supported in *sales, demand or even cash-flow forecasting* as well as in *staff planning activities*. Expert systems are also in use for error and anomaly detection (e.g. Unox, Megara) or the generation of recommendations for customer operations (e.g. Dynamic Yield).

As in other sectors, conversational agents in the form of chatbots or voice-activated assistants are growing in popularity (e.g. de Keyser et al. 2019; Berezina et al. 2019; Adam

et al. 2020). With a large amount of different service solutions, NLP especially transforms front-of-house processes, such as *customer operations* and *reservation* processes. AI-enabled solutions enable immediate assistance at all times and consistency in communication (Berezina et al. 2019). Chatbots allow the ordering of menu items or the reservation of tables or provide valuable information. Besides the automation of service communication, NLP is also used for analytical purposes, e.g. to analyze user comments in *reputation management*. In back-of-house solutions, NLP still plays a minor role. A few service solutions strive to help restaurateurs in *recruiting* or in *monitoring staff communication* (e.g. Quapa, Aggity HR) or assist in *procurement processes*, such as the Matcha Wine chatbot. Further interesting NLP applications include Crystal AI, which aids in *business and finance management* by providing key metrics for managers using a conversational approach.

In contrast to the high interest in academic literature, only 15 robotics vendors were found. As already mentioned by Berezina et al. (2019), robots have so far created more opportunities in back-of-house processes. Their deployment can reduce time for preparation and cooking or increase

**Table 4** Number of AI and robotics service solutions in business processes of the restaurant

	Business process	Number of service solutions
Front-of-house processes $n = 55$	Reputation management	6
	Marketing	7
	Reservation	13
	Customer operations	29
Back-of-house processes $n = 69$	Management: business and finance	17
	Supply chain management	14
	Food and beverage preparation	22
	Human resource management	16

**Table 5** Number of AI and robotics service solutions in business processes using AI capabilities

Business process		Natural language processing	Computer vision	Expert systems	Robotics
Overall		<b>36</b>	<b>23</b>	<b>35</b>	<b>15</b>
Back-of-house processes	Customer operations	13	11	4	6
	Reservation	11	0	2	0
	Marketing	5	0	1	1
	Reputation management	6	3	0	
Back-of-house processes	<b>Overall</b>	<b>35</b>	<b>14</b>	<b>7</b>	<b>7</b>
Back-of-house processes	Human resource management	3	0	13	0
	Food and beverage preparation	3	3	6	13
	Supply chain management	2	5	7	1
	Management: business and finance	3	4	11	0
Back-of-house processes	<b>Overall</b>	<b>11</b>	<b>12</b>	<b>37</b>	<b>14</b>

consistency in food quality or productivity (Berezina et al. 2019). Around 14 robotics vendors (e.g. Da Vinci Kitchen, Cala, or Realtime Robotics) market robots that prepare cocktails or draw beer or create diverse meals, such as burgers or pizza. However, a mere seven robotics vendors are active in front-of-house processes, e.g. in *servicing and order taking*, which is in contradiction to the intense research focus on the interaction between robots and customers (e.g. Lu et al. 2020; Qiu et al. 2020; van Doorn et al. 2017). In this line, industry experts declared that the adoption of service robots in customer processes will take more time than adopting industrial robots due to the range of human intuitive and emotional qualities required in service industries (Berezina et al. 2019; Murphy et al. 2019).

Finally, computer vision capabilities are most often incorporated in innovative self-service checkout systems in *customer operations*. Especially in canteen settings, pre-set food is scanned and payment subsequently automated (e.g. Auvisus or Gastrobotics). Another promising use case is food waste reduction within the supply chain, which has become a key topic for restaurants and vendors. For example, Winnow Vision or Kito, have created innovative solutions to enhance sustainable

business practices. Furthermore, image analyses have been successfully combined with NLP in *reputation management* (e.g. Cloudreputation or Travelappeal). However, biometrics, e.g. in the form of facial recognition has not yet established itself in Europe despite its anticipated potential (Berezina et al. 2019; Oracle 2019). Here, only one solution was detected. Similarly, the use of recipe databases is currently not widespread. Only four AI vendors were active in this field, although first solutions, such as IBM Chef Watson were already developed quite early (IBM 2015).

The deployment of different AI capabilities leads to a divergent role of technology in the redesign of traditional processes. Table 6 demonstrates that the prominent use of conversational agents, self-service technologies and a few robots has the effect that AI and robotics services strongly seek to substitute service employees in the service encounter. 42 vendors position their solutions in a way that AI and robotics services replace the responsibilities of service employees in front-of-house processes. On the contrary, the strong share of expert systems in back-of-house processes is associated with a stronger augmentation of service employees (58 service solutions).

**Table 6** Role of technology in service processes: substitution or augmentation of service employees

Business process		Substitution	Augmentation
Front-of-house processes	Reputation management	0	6
	Marketing	5	4
	Reservation	11	3
	Customer operations	26	2
	Overall	42	15
Front-of-house processes	Management: business and finance	0	17
	Supply chain management	1	14
	Food and beverage preparation	11	11
	Human resource management	0	16
	Overall	12	58

To summarize, different capabilities are deployed by vendors for different business processes with the effect that restaurant operators must take various decisions when redesigning service processes. Functionalities implemented in these information systems strongly impact the redesign of processes and tasks (Davenport and Short 1990; Davenport 1993). Moreover, the diverse capabilities of AI and robotics service solutions affect the future role of service employees so that service managers must need to be aware of these capabilities to successfully design future AI-enabled operations.

### Substitution of human tasks by AI and robotics

Related to the second research question, the progress of technologies in substituting human tasks was analyzed. The theory of job replacement by Huang and Rust (2018) argues that AI will ultimately take over all human tasks on all intelligence levels – from more mechanic to emotional labor. This research strives to provide further empirical data in association with the theory, especially in a high-contact service industry where emotional labor plays a significant role to achieve hospitality (Prentice 2014; Prentice et al. 2020; Rosete et al. 2020).

Table 7 provides an overview of AI and robotics service solutions that have developed solutions for certain subprocesses. Like the results of Chui et al. (2016) a high amount of subprocesses were discovered that require a lower intelligence level and that are automated more easily. Similarly, 94 of all solutions support or execute tasks in subprocesses on a lower intelligence level (mechanical/mechanical-thinking) in comparison to only 24 solutions that assist in thinking and emotional tasks. This is in line with the job replacement theory (Huang and Rust 2018), which expects AI to first replace tasks on the mechanical and thinking level. Solutions that assume tasks on the mechanical level refer to *accounting, ordering, serving, and payment* or *cooking and drinks*. Subprocesses with additional thinking tasks often represent analytical or coordinating activities, such as *staff planning, sales forecasting, or controlling*.

When investigating the application fields of AI capabilities (see Table 8), it becomes apparent that mechanical processes are mainly supported by robotics and conversational agents using NLP. Physical robots were only found in subprocesses with a higher intelligence level. In subprocesses with a high amount of mechanical and thinking tasks, particularly expert systems were applied to assist employees. In emotional-thinking subprocesses, a few AI services implemented NLP to support the *business strategy development* and the *reputation management* in combination with computer vision technologies. Expert systems were also occasionally deployed for processes with a higher intelligence level.

Again, the analysis of the specific role of technologies in supporting or augmenting human employees additionally confirms the theory of Huang and Rust (2018). AI and robotics

service solutions that support subprocesses and tasks on a mechanical level are intended more to replace human work whereas the look at subprocesses with thinking and emotional tasks reveals that most solutions still augment service employees in service process. This could indicate that the development of technologies is not yet as advanced and that the restaurant industry, as a contact-intensive service sector, is at an early stage of the AI evolution.

Nevertheless, about 24 vendors already offer solutions that perform or support analytical and emotional tasks. This contradicts current hospitality literature (e.g. Ivanov et al. 2019; Rosete et al. 2020) which states that AI and robotics are mainly used for functional, repetitive tasks in hospitality processes that lack intellectual and socio-emotional capabilities (Ivanov et al. 2019; Lu et al. 2020; Rosete et al. 2020). Solutions that support subprocesses on the thinking level are currently concerned with *recipe creation* combining different ingredients and flavors based on large recipe databases. Single AI service solutions are integrated in self-service solutions and take over the *consulting and selling* to the customer. Further service solutions were identified in back-of-house processes, i.e. *staff training and development*. The vendor Aggity, for example, has developed, the “Talent Management Service” for *staff development* by analyzing employee profiles, monitoring employee development, and automatically identifying risk candidates through algorithms. This example indicates that emotional labor does not only take place in the service encounter. Instead emotional intelligence also plays a significant role in back-of-house processes in the restaurant sector.

Figure 3 combines the analysis dimensions and offers an overview of the potential of process innovation in the respective business processes along with the role of technology and the different intelligence levels of subprocesses. It shows the number of AI and robotics solutions by means of pictograms and indicates that the potential of process innovation using AI and robotics technologies strongly depends on the respective business processes. For some business processes, AI and robotics vendors offer more AI and robotics service solutions, resulting in different levels<sup>1</sup> of opportunities for process innovation: In processes, such as *customer operations* and *food and beverage preparation*, the potential for innovation is higher whereby processes, such as *marketing*, and *reputation management* are on a lower level. When tapping into the field of AI and robotics, the identification and prioritization of use cases in business processes is a key issue for creating process innovation (Davenport and Short 1990; Davenport 1993; Davenport and Ronanki 2018). Service operators should therefore consider the progress of technologies in specific business processes and their level of potential innovation while identifying the appropriate use case for their

<sup>1</sup> However, the processes under consideration contain a different number of subprocesses (see Table 1) so that a different level of technology advancement could also be biased by the number of subprocesses and related opportunities.

**Table 7** Service solutions categorized by intelligence level, business processes & role of technology

	Intelligence level of subprocesses		
	Mechanical	Mechanical-thinking	Thinking and thinking-emotional
Number of sub-Processes	9	11	12
Total number of solutions <sup>a</sup>	49	45	24
Front-of-house processes	<b>Customer operations:</b> <i>servicing, payment (14)</i> <b>Reservation:</b> <i>reservation retrieval (11)</i> <b>Marketing:</b> <i>campaign execution (4)</i>	<b>Customer operations:</b> <i>customer information, order taking (11)</i> <b>Marketing:</b> <i>menu design, campaign planning (4)</i>	<b>Customer operations:</b> <i>consulting/selling (3)</i> <b>Marketing:</b> <i>segmentation (2)</i> <b>Reservation:</b> <i>table management (4)</i>
Front-of-house processes	<b>F&amp;B preparation:</b> <i>cooking and drinks incl device management (17)</i> <b>Supply chain management:</b> <i>order/procurement management (2)</i> <b>Management: business and finance:</b> <i>accounting (6)</i>	<b>Supply chain management:</b> <i>inventory management, purchase planning (7)</i> <b>Human resource management:</b> <i>staff planning and scheduling (13)</i> <b>Management: business and finance:</b> <i>forecasting and planning, controlling, and reporting (12)</i>	<b>F&amp;B preparation:</b> <i>recipe creation and menu planning (5)</i> <b>Human resource management:</b> <i>recruiting (3), staff training and development (2)</i> <b>Management: business and finance:</b> <i>business strategy (1)</i>
Role of technology			
Substitution	33	34	5
Augmentation	18	12	21

<sup>a</sup> As AI and robotics service providers can support multiple subprocesses, multiple categorizations are possible.

business. Moreover, the future role of technology strongly depends on the intelligence level of the respective subprocesses so that restaurant operators should incorporate the intelligence level into their considerations as well.

## Decision support for service managers

In reference to the research questions, the market analysis generated empirical data for a systematic view on opportunities for process innovation in the restaurant sector and the advancements of AI and robotics service solutions in a high-contact service sector. At the same time, such a systematization of service solutions may serve as the foundation for future conceptual work that supports the industry in strategic decision making.

Service managers need to determine whether and when to benefit from AI and robots that feature a particular intelligence (Huang and Rust 2018). They should also conduct a thorough analysis of alternatives to develop a coordinated plan before redesigning their processes (Venkatraman 1994; Davenport and Ronanki 2018). Decision support can thereby assist service managers in finding the adequate technology and in redesigning future processes for the collaboration of human and artificial intelligence (Larivière et al. 2017; Paluch and Wirtz 2020; Wirtz et al. 2018). At the same time, the review of hospitality and service literature demonstrated that only little research developed conceptual guidance to support service managers in their decision process and future task allocation (Belanche et al. 2020; Huang and Rust 2018; Larivière et al. 2017; Paluch et al. 2020; Wirtz et al. 2018).

**Table 8** AI and robotics service solutions categorized by AI capability and supported subprocesses

AI capability	Intelligence level of subprocesses			
	Mechanical	Mechanical-thinking	Thinking	Emotional-thinking
Natural language processing	16	16	4	8
Computer vision	18	5	0	1
Expert systems	6	21	7	3
Robotics	14	2	0	0

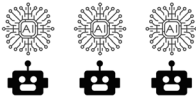

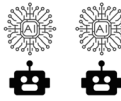

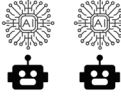
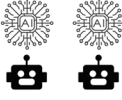
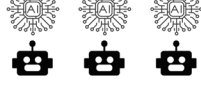
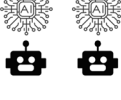
Front-of-House Processes	<p><b>Customer Operations</b></p>  <p>SUB ——— AUG</p> <p><b>Number of Subprocesses</b>                  Mechanical: 2                  Mechanical-Thinking: 4                  Thinking/Emotional-Thinking: 2</p>	<p><b>Marketing</b></p>  <p>SUB ——— AUG</p> <p><b>Number of Subprocesses</b>                  Mechanical: 1                  Mechanical-Thinking: 2                  Thinking/Emotional-Thinking: 2</p>	<p><b>Reservation</b></p>  <p>SUB ——— AUG</p> <p><b>Number of Subprocesses</b>                  Mechanical: 1                  Mechanical-Thinking: 0                  Thinking/Emotional-Thinking: 1</p>	<p><b>Reputation Management</b></p>  <p>SUB ——— AUG</p> <p><b>Number of Subprocesses</b>                  Mechanical: 0                  Mechanical-Thinking: 0                  Thinking/Emotional-Thinking: 1</p>
	<p><b>Back-of-House Processes</b></p> <p><b>Management: Business and Finance</b></p>  <p>SUB ——— AUG</p> <p><b>Number of Subprocesses</b>                  Mechanical: 1                  Mechanical-Thinking: 2                  Thinking/Emotional-Thinking: 1</p>	<p><b>Supply Chain Management</b></p>  <p>SUB ——— AUG</p> <p><b>Number of Subprocesses</b>                  Mechanical: 2                  Mechanical-Thinking: 2                  Thinking/Emotional-Thinking: 1</p>	<p><b>Food and Beverage Preparation</b></p>  <p>SUB ——— AUG</p> <p><b>Number of Subprocesses</b>                  Mechanical: 2                  Mechanical-Thinking: 0                  Thinking/Emotional-Thinking: 1</p>	<p><b>Human Resource Management</b></p>  <p>SUB ——— AUG</p> <p><b>Number of Subprocesses</b>                  Mechanical: 0                  Mechanical-Thinking: 2                  Thinking/Emotional-Thinking: 2</p>

Fig. 3 Number of service solutions, the role of technology, and the intelligence level of subprocesses

This research postulates that process innovation represents a valuable perspective to integrate a process view with the systematic identification of innovation opportunities (Davenport and Short 1990; Davenport 1993). Simultaneously, the business process perspective has the purpose of planning and coordinating operational tasks, clarifying responsibilities and aligning IS technologies to (service) employees (e.g. Davenport 2015). Thus, a perspective on business processes should be adopted that structures the application domain of AI and robotics in service operations and coordinates tasks along business operations.

Previous conceptual work, e.g. the service deployment model, focuses on the nature of tasks as the decision criteria for future task allocation (e.g. Huang et al. 2019; Huang and Rust 2018; Wirtz et al. 2018). Yet they fail to relate tasks and activities to specific business processes. This is important since service managers first need to identify specific opportunities for improvements to consider the use of new technologies. Looking at service solutions in the context of business processes facilitates the identification of use cases and may guide service managers

where to start with applying AI and robotics. Therefore, this contribution proposes an integrated view on business processes and the nature of tasks as the foundation for conceptual models. Following the work of Davenport (1993), it suggests a reference process for the selection of AI and robotics technologies that is demonstrated in Fig. 4.

First, the business requirements and the appropriate use case for AI service solutions need to be identified in specific business processes, e.g. in the subprocess of *staff planning* in *human resource management*. Afterwards, service operators, such as restaurant managers, should define the task portfolio of a subprocess and the level of intelligence, e.g. creating a shift plan. In step 3 and 4, necessary functionalities and AI capabilities of available service solutions, e.g. NLP, will be examined in greater detail and mapped with the corresponding business need (e.g. Hofmann et al. 2020), e.g. optimizing the shift planning. Moreover, service managers are advised to consider strengths and weaknesses of technological capabilities and related consequences for the redesign of processes (Davenport and Short

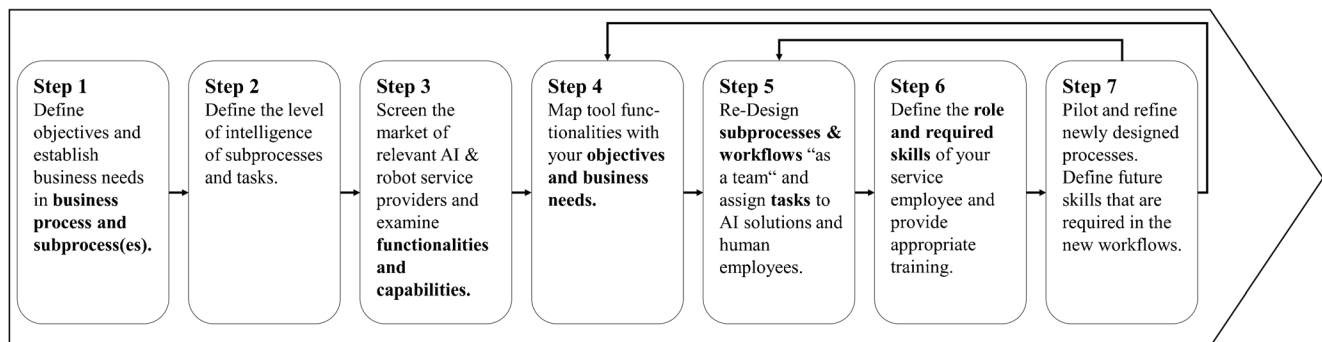


Fig. 4 A reference process for selecting and implementing AI and robot service solutions

1990; Davenport 1993; Davenport and Ronanki 2018). The fifth step addresses the discussion of whether human abilities are still required for the specific task, for example for communicating shifts that are not fitting the indicated timings of employees. Similar to the service deployment model (Paluch et al. 2020; Wirtz et al. 2018), the type of task and its intelligence level defines whether AI or robotics should take over the respective activity or if human and artificial intelligence should collaborate. Humans collaborate with robots and AI, which augments their abilities in high complex analytical and cognitive work settings (Larivière et al. 2017; Paluch et al. 2020; Wirtz et al. 2018). On the contrary, service employees may assist robots or conversational agents, e.g. in sustaining their functionality. Service managers must think of new tasks for service employees as well as creative workflows of human-robot collaboration. Restaurant operators should consider that AI and robotics are also suspect to technical problems. Therefore, new tasks, such as error handling of technologies and robot maintenance arise in processes (Berezina et al. 2019; Ivanov and Webster 2019).

If subprocesses and workflows are more complex, Davenport (2018) suggests using design thinking methods to develop new workflows together with customers and employees. In these redesigned processes, employees require a clear understanding of their novel roles associated with the rising infusion of AI and robotics technologies (Larivière et al. 2017; Lu et al. 2020; Paluch et al. 2020). Novel processes driven by human-robot collaboration offer new responsibilities for service employees, but also complicate the roles of employees, which can result in stress for employees and deviation from newly prescribed processes (Belanche et al. 2020; Christ-Brendemühl and Schaarschmidt 2019). Consequently, managers should prepare their service employees and provide appropriate training. This will allow employees to feel empowered and motivated to meet their new responsibilities (Larivière et al. 2017; Maier and Edwards 2020). The final step consists of piloting the solution: Service operators, such as restaurant managers, should test the AI service solution along with newly defined workflows (e.g. Davenport 1993). If functionalities or the workflow itself are not yet satisfactory, iterations should follow like known from agile methodologies. This piloting phase also offers opportunities to learn about new skills that are required for the new workflow.

## Contributions

Driven by the technological progress of AI technologies, staff shortage, and productivity growth, experts from industry and research expect the rising adoption of AI technologies and the transformation of all service sectors, including the restaurant sector. In accordance with the call for more research on service technologies (Kunz et al. 2019; Wirtz et al. 2018), this

paper analyzed the current European market of AI and robotics service solutions in the restaurant business as a high-contact service sector. Current solutions were screened to generate empirical data for a systematic view on AI and robotics opportunities for process innovation in restaurants. The paper not only provided empirical evidence for the theory of job replacement (Huang and Rust 2018). It also described the characteristics of existing AI and robotics solutions to create a foundation for conceptual work in the field. Four main contributions shall be mentioned:

First, the vertical analysis of a single service sector provides empirical data on how existing AI and robotics technologies already perform human tasks corresponding to business processes and tasks in a high-contact service industry. By taking the restaurant service sector as an example, an early transformation stage of the service sector was investigated. Similar to existing literature (Chui et al. 2016; CUF 2018; Ivanov et al. 2019), the analysis demonstrates that a broad range of subprocesses and tasks in the restaurant sector require skills on a mechanical intelligence level and that the majority of identified AI and robotics service solutions currently assume these activities. Nevertheless, the analysis also identified that about 24% of the solutions assume intellectual or emotional tasks. Even if the quality of these solutions is not assessed in this research, the evolution is already visible that even high-contact service sectors containing emotional tasks will be increasingly overwhelmed by AI technologies. Thus, service operators will be confronted more often with the decision of whether existing service solutions are appropriate for the specific tasks and should strike the appropriate balance between automation and human contact.

Second, with regard to conceptual frameworks, a reference process was proposed to provide first practical guidance: As service literature on the interplay of AI technologies and organizational structures is still in its infancy, the suggested reference process aims at offering entry points for future research. Furthermore, empirical data were provided as the foundation for further conceptual work that can guide service operators in their decisions. In this nascent field, a first knowledge base for future systematization approaches was suggested, which might serve the development of archetypes (e.g. Remane et al. 2016). The combination of analysis dimensions could, for example, examine the maturity level of AI and robotics solutions in subsequent research. Early results indicate that such a maturity level may depend on the type and the number of processes being supported and that about 30 AI and robotics service solutions already provide assistance in multiple business processes and subprocesses. Moreover, the deployment of a mix of different AI capabilities also direct to a certain maturity level of AI service solutions. To attain autonomy, robots incorporate, for example, further capabilities, such as image recognition or NLP (Murphy et al. 2019). The *Barney Bar* from *FP Robotics* represents such an example that has integrated NLP abilities allowing the customer to directly

order from the robot. Future research can continue from this state and examine the maturity level of AI and robotics solutions as a basis for future decision support. Additional analysis dimensions, such as the potential for networked business operations in the restaurant's ecosystem could be relevant. The analysis of platform aspects, i.e. the multi-sidedness, transaction processes or the creation of network effects (Cusumano et al. 2019; Evans and Schmalensee 2016; Alt 2020) can point to the economic stability of solutions and thus represent additional indicators for their maturity. Some service solutions are provided directly by platform providers, such as Open Table, Quandoo or Trip Advisor (La Fourchette). In addition, vendors, such as Matcha Wine, Cortilla or Quapa have created own platform approaches that strive to connect restaurateurs with different stakeholders. The focus on platform aspects may also point to automation potentials between business partners in the restaurant ecosystem, e.g. with restaurant suppliers. Finally, such systematization approaches could not only assist service operators in identifying use cases for process innovation. They could offer guidance for the prioritization of certain technologies based on existing strengths and weaknesses and could be used in future methods to assess the potential of AI and robotics technologies.

Third, a lack of specific research in academic literature opens entry points for future research. Despite the strong emphasis on the service encounter in academic research, the large number of back-of-house solutions highlights the necessity to look at opportunities in all business processes. Back-of-house processes require more attention in academic research, specifically in relation to emotional work (Tambe et al. 2019) and promising potentials of automation and co-creation in networked service systems (Bock et al. 2020). Conceptual work should consider both the service encounter and the back-of-house processes to develop comprehensive guidance for service operators. Furthermore, the intense use of machine learning and automatic reasonings specifically in the application of expert systems underlines the necessity to extend future AI research in the hospitality sector. Besides social and virtual robots, research needs to integrate these applications in their conceptual work. Rosenblat and Stark (2016) as well as Lee et al. (2015) demonstrate, for example, how the use of algorithms for work assignment negatively influences the collaboration between employees in service processes. Inadequately implemented AI service solutions resulted in decreased employee retention and satisfaction in business operations (Lu et al. 2020; Prentice et al. 2020) so that these aspects must be included in the conceptual work for comprehensive decision support.

Finally on the practical side, the analysis reveals several potentials for future AI services as well as opportunities for (new) AI technology providers: First, regardless of large datasets and research in this field (Herranz et al. 2018; Marin et al. 2019; Salvador et al. 2017), commercial applications that combine image and text data for creating recipes are rare. Second, compared

to other sectors, AI service solutions are little present in the restaurant's marketing processes. For example, this refers to automatic content creation. Instead, the MMC Venture report 2019 demonstrated that around 25% of all identified AI solutions in Europe are developed for marketing teams. In contrast, the present analysis only detected 14 AI solutions (11%) that facilitate marketing and reputation management activities. Moreover, robotics or voice-activated agents that create human-artificial co-creation in the kitchen or optimize internal communication were rarely found.

## Research limitations

The primary research objective was the analysis of the current market situation for AI and robotics service solutions in the five largest European food markets. In comparison to other national markets, the first limitation recognizes that these are not always the most innovative countries. For example, MMC Ventures (2019) showed that Sweden and Ireland have developed more AI service solutions than Spain and Italy in other sectors. Thus, additional countries should be examined in future to improve the understanding of the European restaurant market. Second, since the US and the Asian markets are more progressive, a comparison with these markets could also be valuable to reflect the technological progress in different business processes. A third limitation refers to the assignment of AI capabilities to the respective AI vendors. Since available corporate websites and online documentation of vendors were analyzed in detail, these AI vendors do not always fully describe the use of AI capabilities, e.g. the use of computer vision in robotics solutions. This implies that specific capabilities could be underestimated in the study and along the same lines the functionalities and capabilities of AI could be differentiated in more detail (e.g. Dietzmann and Alt 2020). Fourth, further biases could have occurred by the effect of AI washing (Domek 2020) that has been observed recently. This signifies that vendors present their solution as AI technology for marketing purposes although they have solely developed single rule-based systems.

Besides the supplier side, restaurant operators should also be interviewed to collect data on the demand side, similar to the work of Neary et al. 2018. Finally, the completeness and usefulness of the reference process should be assessed in detail and challenged by service operators that could test and take advantage of the reference process. Due to its strong organizational focus, other significant aspects related to AI and robotics have not yet been considered and should be added in future development cycles, e.g. the availability of data for AI services (Hofmann et al. 2020) or topics, such as data security, data privacy issues, or the quality of algorithms (e.g. Berezina et al. 2019).

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## Appendix

**Table 9** The task descriptions are based on the O\*NET database with about 1000 job and task descriptions (c.f. Huang et al. 2019).

Business process: customer operations		
Subprocess	Tasks	Level of intelligence
Customer Information	Getting information (me), processing information (th), evaluating information to determine compliance with standards (th), communicating with persons outside the organization (em)	Mechanical (me) and thinking (th)
Customer service and complain management	Processing information (th), evaluating information to determine compliance with standards (th), making decisions and solving problems (th), interpreting the meaning of information for others (th), communicating with persons outside the organization (em), establishing and maintaining interpersonal relationships (em)	Thinking (th) and emotional (em)
Order taking (inhouse)	Getting information (me), interpreting the meaning of information for others (th), documenting/recording information (me), performing administrative activities (me), monitor processes, materials or surroundings (th)	Mechanical (me) and thinking (th)
Serving	Performing general physical activity (me), handling and moving objects (me), operating equipment (me)	Mechanical (me)
Consulting/selling	Thinking creatively (th), developing objectives and strategies (th), interpreting the meaning of information for others (th), provide consultation and advice to other (th), communicating with persons outside the organization (em), resolving conflicts and negotiating with others (em), selling or influencing others (em), establishing and maintaining interpersonal relationships (em)	Thinking (th) and emotional (em)
Payment	Performing administrative activities (me), documenting/recording information (me)	Mechanical (me)
Online delivery management (order taking & management)	Getting information (me), processing information (th), performing administrative activities (me)	Mechanical (me) and thinking (th)
Capacity & queue management	Getting information (me), controlling machines and processes (me), documenting/recording information (me), monitor processes, materials, or surroundings (th), identifying objects, actions, and events (th), estimating the quantifiable characteristics of products, events, or information (th), processing information (th), evaluating information to determine compliance with standards (th), updating and using relevant knowledge (th), communicating with persons outside organization (em)	Mechanical (me) and thinking (th)
Business process: reputation management		
Subprocess	Tasks	Level of intelligence
Review management (search & reply)	Getting information (me), interpreting the meaning of information for others (th), estimating the quantifiable characteristics of products, events or information (th), processing information (th), analyzing data or information (th), communicating with persons outside organization (em), establishing and maintaining interpersonal relationships (em)	Thinking (th) and emotional (em)
Business process: supply chain management		
Subprocess	Tasks	Level of intelligence
Procurement planning	Scheduling work and activities (me), organizing, planning and prioritizing work (th), performing administrative activities (me), estimating the quantifiable characteristics of products, events or information (th), updating and using relevant knowledge (th), developing objectives and strategies (th)	Mechanical (me) and thinking (th)
Distributor price negotiation	Analyzing data or information (th), communicating with persons outside organization (em), negotiating with others (em), resolving conflicts (em)	Thinking (th) and emotional (em)
Order/procurement management	Performing administrative activities (me), controlling machines and processes (me), inspecting equipment, structures, or material (me), documenting/recording information (me), handling and moving objects (me), communicating with persons outside organization (em)	Mechanical (me)

**Table 9** (continued)

Inventory management incl. planning and controlling & food waste management	Getting information (me), updating and using relevant knowledge (th), documenting/recording information (me), monitoring and controlling resources (th), processing information (th), analyzing data or information (th), monitoring and controlling resources (th), inspecting equipment, structures or materials (me), estimating the quantifiable characteristics of products, events or information (th)	Mechanical (me) and thinking
Hygiene, quality & food security control	Getting information (me), inspecting equipment or material(me), controlling machines and processes (me), documenting/recording information (me), evaluating information to determine compliance with standards (th)	Mechanical (me)
Business process: food & beverages preparation		
Subprocess	Tasks	Level of intelligence
Recipe creation & menu planning	Thinking creatively (th), updating and using relevant knowledge (th), monitoring and controlling resources (th)	Thinking (th)
Cooking & drinks	Performing general physical activity (me), handling and moving objects (me), operating devices, operating equipment (me)	Mechanical (me)
Kitchen device management	Inspecting equipment, structures or materials (me), controlling machines and processes (me), repairing and maintaining equipment (me), interacting with computers (th)	Mechanical (me)
Business Process: Management: Business & Finance		
Subprocess	Tasks	Level of intelligence
Business strategy	Monitor processes, materials or surroundings (th), processing information (th), organizing, planning and prioritizing work (th), judging the qualities of things, services or people (th), updating and using relevant knowledge (th), developing objectives and strategies (th), communicating with supervisors, peers or subordinates (em), guiding, directing and motivating subordinates (em), staffing organizational units (em)	Thinking (th) and emotional (em)
Forecasting & planning	Getting information (me), scheduling work and activities (me), organizing, planning and prioritizing work (th), estimating the quantifiable characteristics of products, events or information (th), updating and using relevant knowledge (th), developing objectives and strategies (th), updating and using relevant knowledge (th)	Mechanical (me) and thinking (th)
Controlling & reporting	Documenting/recording information (me), monitor processes (th), analyzing data or information (th), updating and using relevant knowledge (th), analyzing data or information (th), monitoring and controlling resources (th)	Mechanical (me) and thinking (th)
Accounting	Getting information (me), documenting/recording information (me), performing administrative activities (me), processing information (th), monitoring and controlling resources (th)	Mechanical (me)
Business process: reservation		
Subprocess	Tasks	Level of intelligence
Table management	Processing information scheduling work and activities (me), planning and prioritizing work (th), estimating the quantifiable characteristics of products, events, or information (th)	Thinking (th)
Reservation retrieval	Getting information (me), documenting/recording information (me), performing administrative activities (me), communicating with people outside the organization (em)	Mechanical (me)
Business process: marketing		
Subprocess	Tasks	Level of intelligence
Segmentation	Analyzing data or information (th), processing information (th)	Thinking (th)
Campaign & promotion planning	Developing objectives and strategies (th), organizing, planning and prioritizing work (th), performing administrative activities (me), documenting/recording information (me)	Mechanical (me) and thinking (th)
Design	Thinking creatively (th)	Thinking (th)
Campaign execution (across channels, e.g. social media, email, etc.)	Scheduling work and activities (me), performing administrative work (me), documenting/recording information (me)	Mechanical (me)
Menu design	Documenting/recording information (me), thinking creatively (th)	Mechanical (me) and thinking (th)

**Table 9** (continued)

Business process: human resource management	Subprocess	Tasks	Level of intelligence
	Recruiting	Getting information (me), scheduling work and activities/ performing administrative activities (me), processing information (th), interpreting the meaning of information for others (th), judging the qualities of things, services or people (th), making decisions and solving problems (th), communicating with persons outside the organization (em), staffing organizational units (em)	Mechanical (me) and thinking (th)
	Staff planning and scheduling	Getting information (me), scheduling work and activities (me), performing administrative activities (me), estimating the quantifiable characteristics of products, events or information (th), organizing, planning and prioritizing work (th), updating and using relevant knowledge (th), coordinating the work and activities of others (em), communicating with supervisors, peers or subordinates (em)	Mechanical (me) and thinking (th)
	Staff training and development	Coaching and developing others (em), training and teaching others (em), development and building teams (em), establishing and maintaining interpersonal relationships (em), processing information (th), judging the qualities of things, services or people (th), provide consultation and advice to other (th), communicating with supervisors, peers or subordinates (em), guiding, directing and motivating subordinates (em), staffing organizational units (em)	Thinking (th) and emotional (em)
	Incident management	Monitor processes, materials or surroundings (th), processing information (th), evaluating information to determine compliance with standards (th), resolving conflicts and negotiating with others (em), making decisions and solving problems (th), provide consultation and advice to other (th), communicating with supervisors, peers or subordinates (em),	Thinking (th) and emotional (em)

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