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Employees' perception of robots and robot-induced unemployment in hospitality industry under COVID-19 pandemic

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ABSTRACT

The impact of the pandemic is driving the recent upsurge in service automation and the adoption of service robots in the hospitality industry. As service paradigm and customer expectations shift from conventional customized and personalized services towards a digitalized service environment, such customer orientation may favor using service robots at scales that could render service employees redundant. This study aims to answer the above question by investigating service employees' perceptions of service robots. Data solicited from 405 service employees in the United States of America via Amazon's MTurk were analyzed using structural equation modeling. The result revealed that employees' awareness of adopting and using service robots significantly impacts their perception of robot-induced unemployment. Further, results indicated that the perception of robots' social skills significantly influences service employees' perception of robot-induced unemployment. Employee status was found to moderate the relationships mentioned above. Specifically, entry-level employees perceive the unemployment risk more than managers.

1. Introduction

Hospitality 5.0 refers "to the extension of the modularity, real-time capabilities, virtualization, decentralization and interoperability design principles of Industry 5.0 to the hospitality industry" (Pillai et al., 2021) is swiftly becoming a mainstream concept in the industry. Specifically, contactless automation technology, mobile technology, robotics, artificially intelligent machines, and virtual and augmented reality are gradually but steadily diffusing into the critical guest touchpoints in the guest consumption journey (Luo et al., 2021; Fu et al., 2022). This gradual proliferation of service robots is projected to continue. The market size for Service robots was valued at $295.5 million in 2020, and the hospitality service robots market is projected to grow to $291.74 million by 2026, recording a CAGR of 11.6% from 2022 to 2026 (Technavio, 2022).

Integrating the Internet of Things (IoT) with hospitality robots enables it to perform optimized personalized services without health and safety concerns. This is a crucial driver for the wide adoption of these technologies in the industry. With Hospitality 5.0 - technological influence in the global hospitality workforce and artificial intelligent robot appears as a convenience, productivity, and human-robots interaction (Pillai et al., 2021; Parvez et al., 2022). The inclusion of robotics and its application in the service industry as "intelligent physical devices" is surging (Lu et al., 2019). These surging interests in the adoption and use of artificially intelligent robots in hospitality, though they present their advantages, a looming concern for many actors in the industry lies in the potential of robots to result in permanent unemployment for many service employees in the long run (Koo et al., 2021).

At the time of finalizing this research output, the application of robots in tourism and hospitality services is evident in areas such as pre-arrival (Chatbots, virtual reality), arrival (robotic porter service, digital kiosks, smart room key), stay (automatic check-in through apps, front desk robot service, delivery robots, vacuum cleaning robots, room assistant), departure (porter robots, travel assistant, express checkout, digital kiosks), assessment (AI platform) (Ukpabi et al., 2019; Choudhury, 2021; Koo et al., 2021). With the emerging new realities of increasing service digitalization in the wake of the pandemic, robotic adoption is amplified, and it is forecasted to continue for the foreseeable

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future (Zeng et al., 2020; Parvez et al., 2021).

Beyond digitalization, other service concepts, such as contactless services with highly reduced human interaction, are becoming more prioritized by hoteliers and consumers (Koumelis, 2020). Lin et al. (2021) concluded that the impact of the pandemic has resulted in a paradigm shift in customer expectations from highly customized services to low or no-contact services as safeguards against infection. These new realities and technological advances open a new world of opportunity for the adoption and use of service robots. In Vatan and Dogan's (2021) view, technological developments such as service robots have the inherent potential to eliminate fear and negative perceptions in hospitality services.

Early scholars in service robotics concluded that service robots offer a viable alternative for hospitality and tourism (Boztas, 2017; Ivanov et al., 2020; Luo et al., 2021). In practice, full robotic service such as those obtainable at the Henna Hotel in Japan, Alibaba Hotel in China, Wynn Hotel, Aloft Hotels in the USA, and Comfort Xpress Hotel in Oslo underscores the potential that service robots can fulfill within the newly emerging hospitality services cape (Gallego et al., 2020). Further, the early adoption of robotics in the industry has seen it used in border controls, mobile boarding passes, biometric check-in and checkout at airports, facial recognition, and automated conveyor systems in restaurants (Lukanova, and Ilieva, 2019; Vatan and Dogan, 2021).

With the growing adoption of robotics in the industry, as well as the findings of McKinsey Global Institute, which suggest that between 400 and 800 million employments in the industry is expected to be powered by robotics application by 2030 (Bowen and Morosan, 2018), understanding service employees' perception of adoption robotics is more critical than ever if they must be motivated to deliver optimal services while on the job (Koo et al., 2021). To date, hospitality scholars have emphasized the importance of service employees to the survival and sustenance of the industry (Lasisi et al., 2020). The notable exception, Ivanov et al. (2018) denoted that employees might resist working with the service robot as they might see them as a threat, while Lu et al. (2019) believed that collaborating with a service robot can have adverse effects like frustration, discomfort, and confusion for service employees. Service robots are generally programmed for information delivery and support employees at the workplace rather than offering service in F&B, catering, checking, and security (Tussyadiah, 2020).

However, researchers and practitioners have emphasized the essential role of robots in the service industry have a positive impact on productivity and customer satisfaction (Lu et al., 2019), which directly affect the organization's structure, culture, decision-making processes, and employment (Xu et al., 2020). As with a new high-tech revolution, organizations must balance the prospects provided with the pressures assigned to current organizational procedure and policy (Choi and Ruona, 2011). Even though in hospitality and tourism literature, artificial intelligence (AI), machine learning, and robotics are not only emerging topics but also there is little research on employee's perception of service robots and how service robots impact hospitality management performances on robots' adoption and employment decision making (Xu et al., 2020; Vatan and Dogan, 2021). However, it is necessary to acknowledge employees' beliefs and understanding about service robots and how robots may affect their employment in the hospitality industry. Therefore, the current study was developed to empirically test a conceptual model that investigates the employee's perception of robot-induced unemployment via the lenses of employees' perception of robot adoption and the moderating role of employees' status. Furthermore, we checked whether being at the entry-level or managerial level affects the direction and strength of employees' perception of robots on the service robots. We believe this study fills the gap in the literature and contributes effectively to employment decision-making strategy besides practical implications that were advanced from the study's empirical findings.

2. Literature review

2.1. Hospitality 5.0 and robot restaurants

The term "Hospitality 5.0″ originated from Industry 5.0 (Pillai et al., 2021). Industry 5.0 specifically indicates actual abilities, modularizes, interchangeability, actualization, and transformation that can diversify any industry to extend the lead to technologically advancement activities. Therefore, the 5.0 hospitality industry aimed at diverting to hospitality 5.0 (Madsen and Berg, 2021). Hospitality 5.0 may influence the hotel industry's high-tech adoption, and during COVID-19 technological use was increased dramatically in hospitality service (Zeng et al., 2020) due to contactless services and safety in customer journey touchpoints (Pillai et al., 2021). Specifically, COVID-19 enhances the use of service robots as a helping hand to provide necessary services to consumers and employees. For instance, the restaurant industry uses service robots as a waiter, chefs/cooks, and drones to deliver food and drinks (Yu, 2020; Parvez and Cobanoglu, 2021; Varlamov, 2021). Therefore, restaurants' technical application of modularity, particularly service robots modular, is a major strategic transformation toward hospitality 5.0 for delivering superior service personalization (Pillai et al., 2021).

The restaurants that employ robots to provide the leading service are called 'robot restaurants' (Borghi and Mariani, 2021; Guan et al., 2021). In the pandemic period, the hospitality industry faced a troubling shortage of employees. Due to rising risk factors, employees shifted to other professions, so labor costs in the restaurant and hotel industry have increased. However, employees' commitment and dedication decreased, motivating restaurant and hotel authorities to adopt robots to ensure safety (Parvez, 2020). Robots' operations in restaurants will progressively rise (Jang and Lee, 2020). According to Varlamov (2021), a robotic cafe, or "Robocafe," emphasizes the expertise of the "Mivar" (logical decision-making kernel) management system. This robotic system mainly works on reception orders for servicing, relevant orders' formation, and delivery. The restaurant of Alibaba hotel in China uses mobile robots R2D2-style to deliver food, drinks, and fresh towels upon command (Devitt, 2019). The author also mentioned that this type of robot also performs as a bartender and can prepare coffee and up to 20 different cocktails. On the other hand, the existence of robots in restaurants may induce some risks (privacy, financial, time, performance, psychological) that can negatively affect the attitudes and intentions of customers (Hwang et al., 2021). Furthermore, robots are perceived as a threat that may lead to unemployment (Vatan and Dogan, 2021) and adverse outcomes due to job insecurity (Koo et al., 2021; Lu et al., 2020).

2.2. Employees' perception of service robots

In psychology, perception refers to "…positive or negative assessments of thinking's objects. Besides perception is the self-possessed effect of the object towards the feelings, and behaviors towards an object in a certain way (Weiten, 2004)". In other words, perception can be regarded as an individual's perceived capacity for thought, morality, emotion recognition, and self-adoption (Stafford et al., 2014). Concerning robotics, perception refers to service employees' psychological activities connected to the adoption or otherwise of robots. More specifically, service employees' perception of robots is their attributed values and behaviors towards using robots (Rantanen et al., 2018; Koo et al., 2021).

In a recent study, Van Looy (2020) concluded that employees' perception of robots reflects the management's trust in adopting and implementing robots in the organization. His findings further suggest that employees' self-confidence and motivation also determine their perception of robots. Similarly, Granulo et al. (2019) and Luo et al. (2021) found a significant linkage between employees' perception of job security and their perception of adopting robots, indicating an inverse correlation between confidence level in job security and perception of robot use. According to Rantanen et al. (2018), employees' communication behavior in human-robot collaboration also indicates their perception of robots. They also showed that employees prefer to work with human colleagues because they should be replaced by human communication and colleagues. However, employees select robots as a replacement when it approaches their employment.

Wang and Wang (2021), in their survey of literature on the use of robotic technologies during the COVID-19 pandemic, found that service robots were suggested to be adopted as a replacement for face-to-face services at restaurants, hotels, and airports to maintain social distancing and protect both guests and employees from infection. Kim et al. (2021) concluded that the COVID-19 pandemic had changed consumers' preferences in that the robots service is more preferred and accepted than human service in hotels. Kazandzhieva and Filipova (2019) pointed out that users of robots differ from "robophobes" to "robophiles," where positive feeling indicates "robophiles" and negative perception of robots specify "Robophobes" an uncomfortable and threatened to feel of robotic advancement in hospitality and tourism. Therefore, the perception of robots can be positive, negative, or neutral in using service robots in tourism and hospitality services. However, the employee's perception of the employment of robots in hospitality is critical (Ivanov et al., 2020; Koo et al., 2021).

In 2016, Travel Zoo conducted a global survey to examine people's perception of service robots in nine countries. The results confirm that 80% of respondents believe that more robotic services will soon be available in travel, tourism, and hospitality (Kazandzhieva and Filipova, 2019). The overall image is that technological advancement and perception of robots do not mean using machines to replace human labor. However, it is the technical use in task accomplishment by human assistance (Ivanov et al., 2020).

2.3. Robot induced unemployment

Technology-induced unemployment became acquainted in 1930 by Maynard Keynes as an economic perception, and the author also mentioned that in the future technological unemployment will infect humanity (Keynes, 1930). In recent times, this thought is more specifically known as robot-induced unemployment. Robotic unemployment can be defined as jobs taken by robots. Pol and Reveley (2017) explained the $R(t+1) - R(t) > H(t+1) - H(t)$ formula to identify robotic unemployment, where the number of jobs taken by robots in $R(t+1)$ is greater than the number of positions taken by humans in $H(t+1)$. According to former studies, robotic advancement directly impacts unemployment; directness's negative and substantial influence on unemployment is comparatively more significant, specifically during and post-pandemic periods (Du and Wei, 2021). According to Keynes : p-325) (1930), "We are being affected with a new disease of which some readers may not have heard the name, but of which they will hear a great deal in the years to come – namely, technological unemployment." COVID-19 is one of the main reasons for decreasing employment, whereas increasing the use of robots (Parvez et al., 2021). Therefore, the robot that induces unemployment is a challenging concept.

According to the OECD (2021), the unemployment rate in different countries is higher than before, such as Australia at 5.70%, European Union (27 countries, 2020) at 7.50%, and the United Kingdom at 5.00%, the United States at 6.10%. Regarding social distance and other infectious protective issues, local labor shortage, and high costs, the annual average wage turns out to be positively and significantly related to unemployment. In reverse, robots introduce proxies' employees in some industries and display a positive and significant effect on unemployment through their cost-saving mechanism (Du and Wei, 2021). Civelek and Pehlivanoğlu (2020) point out that robotic adoption and productive growth directly affect productivity growth, decreasing employment. Robots' challenges may soon influence unemployment and switch some jobs to skill levels (Granulo et al., 2019; Bessen et al., 2020).

2.4. Hypotheses development

2.4.1. Perceived advantages of robots

Once, robots had been used for high-volume industrial purposes, from metal forging to plastic processing. However, with the development of technology, robots' ease of use and affordability allowed big to small-sized organizations to use robots. Perceived advantage is known as flexibility of the TAM model; it is measured as a consequence of procedure and imitates the essential inspiration to accept technologies. In this case, the robot's advantage is necessary to socialize the robot in the service industry (Schmude et al., 2018; Ivanov et al., 2018). The perceived advantage of robots can be a highlight in disasters and crises, where human life is easily identified as endangered (Bishop, 2006; Luo et al., 2021). In the tourism and hospitality service, the idea of quality is positively expected and powerfully correlated with perceived value (Steinfeld et al., 2006; Zhong et al., 2020).

In the post-pandemic period, the use of robots in hospitality has become more critical than ever because random people's close contact triggers the highly contagious virus crisis of COVID-19. In this situation, scientists suggested maintaining social distance, so maintain social distance and providing good service. Service robots can be the alternative solution to offer services and not get virus infection. As a result, experts are willing to use robots in hospitality services from checking in, welcoming guests, navigation, service delivery, and checking out (Parvez, 2020). Nevertheless, the robot advantage is swiftly fully-fledged, with diverse robots performing COVID-19 in several situations, including transportation, airports, hotels, restaurants, recreation, and scenic areas (Lin et al., 2021).

According to Yanco et al. (2004), the positive advantage of robots may even emulate human intellect and performance, which support the robots' recognition to motivate the visitors to receive the mechanized service. Moreover, scholars have categorized human-robot collaboration or contradiction into three classifications: human-centered approaches, robot-centered approaches, and robot cognition-center approaches (Sinha et al., 2020; Zhong et al., 2020; Parvez et al., 2022). Scholars mentioned that service robots could have a unique advantage over human employees, and robots can make appliance alterations in code of behavior with the identical swiftness, consistency, and efficacy (Ullman and Malle, 2019; Zhong et al., 2020), so our proposed hypothesis 1 is:

H1. *: There is a negative and significant relationship between the perceived advantages of robots and robot-induced unemployment.*

2.4.2. Previous experience with robots

Robotic (automatic) service is available in almost every industry; the hospitality and tourism industries are major industries offering tangible and intangible automated services. Currently, robots are used in nearly every department in the hospitality industry, such as the front office to restaurant services (Ivanov et al., 2020; Vatan and Dogan, 2021). Moreover, some hotels have started using robots for virus-killing and housekeeping purposes (Kazandzhieva and Filipova, 2019; Parvez, 2020). Nowadays, robots seem to be proposing an excellent service comparable to or even more significant than human employee service (Vatan and Dogan, 2021). In this situation, robots are as flattering as the challenger to humans' employment in the job sector (Sinha et al., 2020). On the other hand, some scholars also mentioned that robots would be supportive, and human-robot collaboration may run a semi-automatic industry. However, employees' robotic experience in the organization always is not positive (Liu, and Hung, 2020).

Moreover, COVID-19 enhanced robotic service in the hospitality industry, which concerns a threat to employment (Kim et al., 2021). According to Gockley et al. (2007), robots in the workplace might positively or negatively influence negative inflation demonstrated with sentiments of nervousness, escaping, anxiety, assertiveness, and awareness. Therefore, employees suffer anxieties concerning their discretion and unemployment (Lasisi et al., 2020), which leads to technophobia; in that way, employees are unwilling to receive robots. Hence, hypothesis 2 is:

H2. *: There is a negative and significant relationship between previous experience with robots and robot-induced unemployment.*

2.4.3. Social skills of robots

Service robots rise under the attention of artificial intelligence agents, and customers join up more with robots, while social communication evaluation is the identical valuation apparatus of human employees (Ivanov et al., 2018; Lukanova and Ilieva, 2019; Koo et al., 2021). However, in hospitality tourism and travel, robots are cast-off to assist consumers or travelers in providing guidelines, automatic checking in and out, carrying conveniences, washing, and offering security and safety amenities (Kazandzhieva, and Filipova, 2019). Hospitality robots are different from industrial robots; these robots emphasize dealings with humans intelligently, as well as these robots, including speaking, turn-taking, regard, and gesture (Zhong et al., 2020).

H3. *: There is a positive and significant relationship between the social skills of robots and robot-induced unemployment.*

2.4.4. Robots awareness

At present, robots are being used in restaurants, hotels, and airports for many purposes like delivering items, rendering concierge, carrying luggage as front house service and cooking, dishwashing, housekeeping, and other manufacturing tasks in the back (Devitt, 2019; Luo et al., 2021). Moreover, vacuum robot's mobile app for housekeepers, Dishcraft's commercial robotic dishwashers, burger-flipping robot "Flippy," "BreadBot" robot for automated bread, robotic vending machines for food and salad preparation, and Royal Caribbean's Bionic Bar all are different kinds of employed service robots in hospitality and tourism (Vatan, and Dogan, 2021). Ivanov et al. (2020) stated that the robot is an asset of the hospitality organization, creating value for the shareholders and generating financial performance. Also, robots can perform 24/7 without any motivation or additional cost.

On the reverse, employees require a high level of organizational support and motivation with different demands such as (tips, bonuses, 1.5% additional salary for overtime, health insurance, work permit, and vacation), so management prefers to adopt robots in some specific work positions (Sinha et al., 2020). Therefore, robot adoption in the workplace increases the awareness of employees. This awareness increases turnover intention, and turnover intention could be decreased by employees' awareness regarding the number of managerial cares about their embryonic specialized objectives and profits for the workplace (Li et al., 2019; Vatan and Dogan, 2021; Van Looy, 2020). Critical assets are skilled employees in travel, tourism, and hospitality. However, robots in service areas increase awareness and fears of job loss among employees, or thinking of working with robots (machines) increases negative perception and anxiety toward robots (Brougham and Haar, 2018; Acemoglu and Restrepo, 2018; Granulo et al., 2019; Manthiou et al., 2020). Therefore, we proposed hypothesis 4:

H4. *: There is a positive and significant relationship between robot awareness and robot-induced unemployment.*

Employment status (entry-level and managerial level) is a section of an occupation orientation (Burr et al., 2015), which is supposed to adversely impact psychology in a robotic working environment (Granulo et al., 2019). Individual employees clarify the contribution of ed-tech services because incorporating service robots into employees' employment has been impeded by several features (Du and Wei, 2021). In the post-pandemic period, the complexity of labor brought the circumstances of robotic use in the service industry, and these service robots enhanced the fears of robotic unemployment (Jaradat et al., 2020; Hao, 2021; Vatan and Dogan, 2021). McClure (2018) revealed that robotic unemployment would gradually increase in the next few decades. Moreover, Walczuch et al. (2007) describe that employees' skillfulness, experience, and knowledge have the most remarkable impression on the perceived ease of use and perceived usefulness of the required and most used robots. Consequently, unemployment and job insecurity relate to employees' perception of robots and technological skills. Fig. 1.

Besides, employee personalities and their position in the organization may differentiate the impact of robot adoption in their workplace. Employees' attitudes and perceptions toward robots in the workplace vary based on their employment status (Gnambs and Appel, 2019; Khaliq et al., 2022). In this condition, robot adoption may highly impact entry-level positions like receptionist, server, housekeeper, and kitchen helper compared to management-level jobs (Vatan and Dogan, 2021). Therefore, robots' essentiality and recognition in hospitality and tourism characterize a new study area and the desire to integrate Human-Robot-Collaboration (Acemoglu and Restrepo, 2018; Parvez et al., 2022). The collaboration between entry-level employees/skilled level employees and robots stimulates an extremely competitive psychological climate (CPC) subsists. Consequently, employees expect management to play a role in the CPC within the hotel setting to moderate the robotics awareness and motivate them to collaborate with robots instead of turnover intention (Li et al., 2019; Van Looy, 2020). Hence, our hypothesis 5 is:

H5. *: Employment status will moderate the employees' perception of robots on robot-induced unemployment.*

2.5. Methodology

2.5.1. Measures

All the respondents were given survey instruments consisting of questions about their perception of the advantages of service robots, previous experience of using service robots, disadvantages of service robots and the perceived robot-induced unemployment, and demographics. The scale items were measured on a 5-point Likert scale anchored from 1- Strongly Disagree to 5 – Strongly Agree. As part of the precursory approach to ensure the validity of the survey instrument, all items were adapted from previous studies:

- Five items of perceived advantages of service robots, three items of previous experiences of using service robots, two items of perceived social skills of robots, and disadvantages of service robots were taken from Ivanov et al. (2018).
- Four items of robot-induced unemployment were adapted from Jaradat et al. (2020).
- Two items of robot awareness were taken from Brougham and Haar (2018).

2.5.2. Sample

As the precursor to the actual data collection, a pretest was conducted with a sample of 140 individuals representing 10–15 individuals for each measurement item. This pretest was done to ensure the validity of the survey instrument (Hair et al., 2006). To be eligible to participate, an individual must be actively engaged in hospitality service and have had at least one service robot experience in one year. All participants are 18 years or older. Collected data from the pilot test revealed that the survey instrument had face validity.

The primary data for the study was collected from Amazon's Mechanical Turk (MTurk), which can opt-in to investigate independently in reappearance for an insignificant advantage. The advantage of MTurk is that it keeps participants' obscurity and confidentiality. According to Jaradat et al. (2020), MTurk may offer pronounced prospects for organizational investigation models. More importantly, MTurk has been widely used and accepted in hospitality studies (Birinci et al., 2018; Nanu et al., 2020; Cobanoglu et al., 2021; Lu et al., 2021). Moreover, the context of the study is service automation and robotics; hence, an online data collection approach such as MTurk seems appropriate.

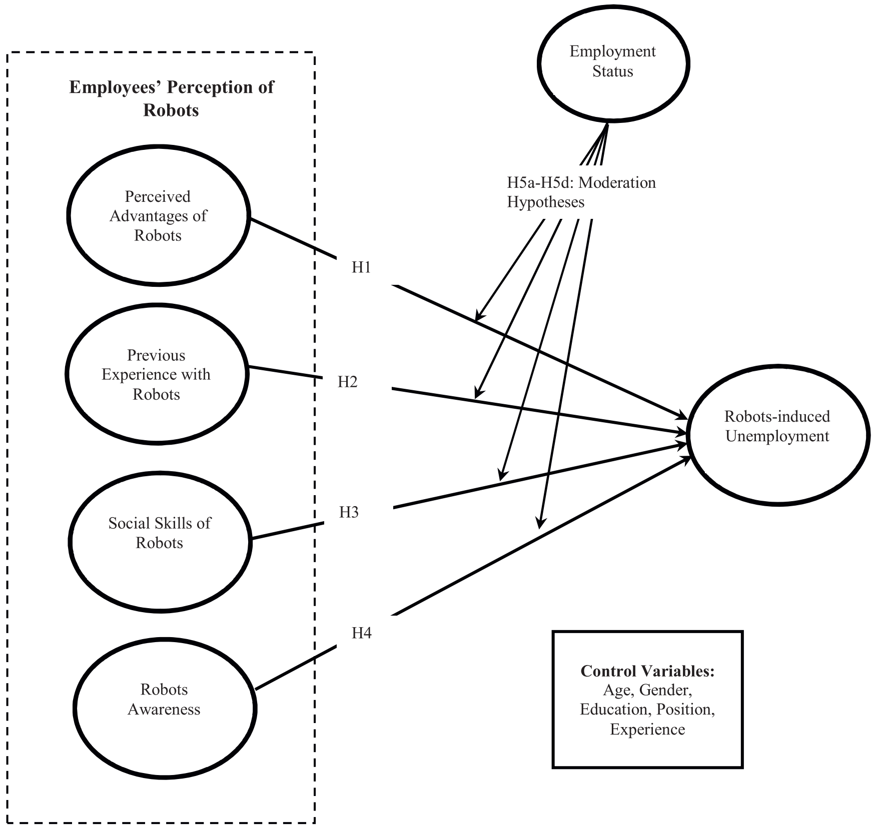

Fig. 1. Conceptual Model.

2.5.3. Data cleaning and test of statistical assumptions

A total of 500 questionnaires were received from MTurk. However, before estimating the measurement and structural models, we cleaned data by eliminating responses with missing data (Osborne, 2013). The attention check questions were added to the survey to ensure the data's validity and reliability, as Cobanoglu et al. (2021) suggested. All respondents who failed these attention check questions were removed from the data set. For example, the age of the participants was asked in two different forms. At the beginning of the survey, the age of the respondents was asked, while at the end of the survey, the birth date of the respondents was asked. The respondents who answered these questions differently for more than two years were eliminated from the study. In addition, a bot check tool was used to prevent bots from taking the surveys (i.e., humans need to click on the circles with traffic lights). After this cleaning, a net of 405 respondents was used for the final analysis.

Further, we ensured that the data satisfied the normality assumption for multivariate analysis by performing skewness and kurtosis checks on the data (Kline, 2011). To ascertain the adequacy of the sample size, we employed Westland's (2010) sample adequacy analysis with our model consisting of 6 latent variables and 17 indicator variables with 0.05 significance at 0.80 statistical power. Westland's algorithm indicated that 227 samples are required as a minimum sample size. Therefore, our sample (405) satisfies the minimum sample size for data adequacy (Westland, 2010). Concerning response rate, since data collection was done via Mturk, it is not possible to have an actual response rate. However, according to Ali et al. (2021), an explanation of data adequacy should be done in cases like this where the response rate cannot be calculated (p.116).

The absolute value of Skewness and kurtosis ranged from −0.672–0.534 and −0.487–1.356, respectively. These values fall within the acceptable threshold of Skewness < 3 and Kurtosis < 8 (Kline, 2011). Therefore, the data satisfied the assumption of normality for multivariate analysis. In addition, several techniques were used to ensure the data was reliable. As Cobanoglu et al. (2021) suggested, several attention check questions were placed in the survey. The respondents who failed these attention check questions were removed from the analysis. Finally, the CAPTCHA tool was used to detect any bots that may have been used to reply to the MTurk surveys.

2.5.3.1. Common method variance. To avoid the issue of method bias in this study, we implemented some procedural preventive measures as recommended by Podsakoff et al. (2003). Firstly, a pilot study was conducted to confirm that the survey questions were worded and understandable. Secondly, we introduced and achieved psychological separation using different cover stories for each survey section. Thirdly, identity questions were not asked, and assurance of anonymity and confidentiality was given to all participants. Finally, we checked our data statistically following Harman's single factor procedure. Accordingly, our non-rotated factor analysis result for the 6 factors showed that all factors explained 80% of the variance while the first factor only accounted for 29.8%. This result indicated that common method variance is not a concern for this study. Further, the inter-construct correlation presented in Table 4 shows no correlation value above 0.9. The highest inter-correlation of 0.78 indicates that common method bias is not a serious concern for this study.

2.5.4. Data analyses

Descriptive statistics and frequency analysis were conducted with Statistical Package for Social Sciences (SPSS), version 26. After data cleansing and eliminating missing data, 405 usable cases were retained for the study. Of these 405 respondents, 55.3% (224) were male, and 44.7% (181) were females. An overwhelming 81.7% (331) worked for wages, while 18.3% (74) were self-employed. The respondents were almost evenly spread across the age groups. The most age representation was 24.2% (98) for people aged 24–29 years, and the least represented was 1.2% (5) for 65 years and older groups. The complete demographic statistics of the respondents are given in Table 1.

2.5.5. Measurement model

Scale validity, including convergent and discriminant validity, was performed via confirmatory factor analysis (CFA) to analyze moments of structures (AMOS) version 24. The CFA was intended to converge 16 items into five constructs. After deleting two items (one from the perceived advantages of robots' scale and the other from the robot awareness scale), the remaining 14 items loaded with standardized loadings greater than 0.5 and loaded under their underlying construct.

All average variance extracted (AVE) for the five factors was greater than 0.5 except for robot awareness and perceived advantage of robots with marginally lower AVEs of 0.40 and 0.42, respectively. According to Hair et al. (2021, p. 77), instead of immediately deleting indicators when their loading is below 0.70, researchers should explore the implications of indicator removal on other metrics of reliability and validity. In general, indicators with loadings between 0.40 and 0.7082 should only be considered for removal if removing the indicator increases the internal consistency reliability or convergent validity beyond the specified threshold value. Content validity, which refers to the extent to which a measure represents all aspects of a particular construct, is an additional factor to examine when deciding whether to delete an indication. Consequently, weaker indicator loadings are occasionally kept. However, indicators with extremely low loadings (below 0.40) must always be removed from the measurement model (Hair et al., 2022). The reliability of the five constructs was greater than 0.6 except for robot awareness, with a marginal reliability value of 0.57. This finding led to the conclusion to retain the 14 items and five constructs for the study (see Table 2).

Discriminant validity was determined by comparing the square root of AVEs with the correlations of the constructs (Fornell and Larcker, 1981). To affirm the presence of discriminant validity, the square root of AVEs must be greater than the correlation estimates of the constructs. As reported in Table 2, the value of the square root of AVEs was greater than the correlation estimates. As a result, the validity of our scale was confirmed.

The model fit statistics of the proposed model further suggest the adequacy of our measurement model for structural analysis. As provided in Table 3, the ratio of chi-square (x^2) to the degree of freedom (df) was

Table 1
Sample demographic statistics (n = 405).

Demographics	%	Frequency
Gender		
Male	55.3	224
Female	44.7	181
Age		
18–23 years	15.1	61
24–29 years	24.2	98
30–34 years	19.3	78
35–44 years	23.5	95
45–54 years	11.1	45
55–64 years	5.7	23
Age 65 or older	1.2	5
Education		
High School	11.4	46
Diploma (2 years)	15.8	64
Bachelors	51.4	208
Masters/PhD	19.8	80
Others	1.7	7
Working Status		
Self Employed	18.3	74
Working for Wages	81.7	331
Experience in Current Work		
6 months to 2 years	39.0	158
3–5 years	32.6	132
6–10 years	13.8	56
More than 10 years	14.6	59
Total Work Experience		
1–3 years	31.9	129
4–6 years	26.2	106
7–9 years	11.6	47
10 years or more	30.4	123
Position		
Entry-level	23.7	96
Skilled level	39.5	160
Management	32.1	130
Others	4.7	19

Table 2
Confirmatory factor analysis.

Variable	Measurement item	SL	CR	AVE	α
RAT			.67	.42	0.67
RAT1	Robots will provide more accurate information than human employees	.60			
RAT2	Robots will be able to provide information in more languages than human employees	–			
RAT3	Robots will deal with calculations better than human employees	.56			
RAT4	Robots will be faster than human employees	.75			
REX			.85	.66	.85
REX1	Being served by robots will be an exciting experience	.88			
REX2	Being served by robots will be a pleasurable experience	.80			
REX3	Being served by robots will be a memorable experience	.75			
SSOR			.81	.69	.81
SSOR1	Robots will be more polite than human employees	.75			
SSOR2	Robots will be friendlier than human employees	.90			
RUE			.91	.70	.91
RUE1	I think my job could be replaced by robots	.78			
RUE2	I am personally worried that what I do now in my job will be able to be replaced by robots	.89			
RUE3	I am personally worried about my future in my organization due to robots replacing employees	.85			
RUE4	I am personally worried about my future in my industry due to robots replacing employees	.84			
RAW			.57	.40	.57
RAW1	Robots will be able to recover dissatisfied guest	.56			
RAW2	The use of robots eliminated many jobs	–			
RAW3	Robots distract me from performing my work duties jeopardizing my job	.69			

Note. SL = Standardized Loading, CR = Composite reliability, α = Cronbach's Alpha, RAT = Perceived Advantage of Robots, REX = Previous Experience with Robots, SSOR = Social Skills of Robot, RUE = Robot induced unemployment, and RAW = Robot Awareness, (-) = item deleted during CFA.

Table 3
Goodness of Fit Indices.

The goodness of fit indices	Index		Cut off Criteria
	Before	After Modification	
$CMIN^2$/df	3.85	3.15	≤ 5
Normed Fit Index (NFI)	0.89	0.93	> 0.90
Comparative Fit Index (CFI)	0.90	0.95	> 0.90
Tucker-Lewis Index (TLI)	0.90	0.93	> 0.90
Root Mean Square Error of Approximation (RMSEA)	0.08	0.07	< 0.08
Standardized Root Mean Square Residual (SRMR)	0.09	0.08	≤ 0.08

Note: cut-offs from Bentler, 1990; Tucker & Lewis, 1973; Steiger, 1990; Joreskög &Sörbom, 1988

Table 4
Discriminant Validity test using the square root of AVE and Correlation.

	Constructs	Square root of AVE	1	2	3	4	5
1.	Perceived Advantages of Robots	0.65	–	.51***	.31***	.19*	.25***
2.	Previous Experience with Robots	0.81		–	.55***	.32***	.22***
3.	Social Skills of Robots	0.83			–	.59***	.37***
4.	Robot-induced Unemployment	0.63				–	.78***
5.	Robot Awareness	0.84					–

Note:
* $p < 0.100$
*** $p < 0.001$.

3.15, which is lesser than the upper threshold value of 5, and the comparative fit index (CFI) = .95, Tucker-Lewis fit index (TLI) = 0.93, root mean square error of approximation (RMSEA) = .07, Standardized root mean square residual (SRMR) = .08 all indicated a satisfactory model fit (Kazandzhieva, and Filipova, 2019). Table 5.

The result from the structural model indicated that RAT does not significantly influence an individual's perception of RUE ($r = 0.19$, $p = 0.10$) ($\beta = 0.070$, $t = 1.187$, $p = 0.236$); thus hypothesis 1 is rejected. Similarly, REX does not empirically influence people's perception of RUE ($r = 0.32$, $p = 0.000$) ($\beta = 0.050$, $t = 0.826$, $p = 0.409$); hence, hypothesis 2 is rejected. Contrarily, the empirical results showed that SSOR significantly and positively influence RUE ($r = 0.37$, $p = 0.000$) ($\beta = 1200.229$, $t = 4.600$, $p = 0.001$); and RAW equally significantly predicts RUE ($r = 0.78$, $p = 0.000$) ($\beta = 0.449$, $t = 10.120$, $p = 0.001$). Both SSOR and RAW together explain R^2 $(_{RUE}) = 36\%$ of variance. Hence, hypotheses 3 and 4 received empirical support.

2.6. *Testing moderating effect of employment status*

To test the moderating effect of employment status, we followed the recommended multiple-group chi-square difference test between constrained and unconstrained models (Jöreskog and Sörbom, 1993). As a first step, the data ($n = 405$) was divided into two employment status groups (skilled/entry-level and managerial-level). Table 6 is used to document the result of the multiple-group analyses. As noted, the differential effect of employment status between the skilled level employees and the managerial level employees through the examination of the degree of freedom between the fully constrained model and the unconstrained model (Anderson & Gerbing, 1988) was significant ($\Delta\chi2 = 28.69$, $\Delta df = 12$, $p < .01$) suggesting that, in the two groups, the direct effect of the predictors of RUE differs based on the status of employment.

Further, we performed multiple-group analyses for each parameter pair to ascertain which path(s) significantly differs based on employment status. As shown in Table 6, two of the predictors showed a significant difference between the groups, suggesting that employment status moderates significantly the relationship between these predictors and RUE. Specifically, employment status significantly moderates the intensity of the effect of RAW on RUE ($\Delta\chi2 = 9.65 < \chi2_{.05(1)} = 3.84$, df $= 2$, $p < 0.001$) and between social skills of robots and RUE ($\Delta\chi2 = 5.79 < \chi2_{.05(1)} = 3.84$, df $= 2$, $p < .001$). A pairwise parameter comparison test was conducted to confirm the significance of these results, and the resulting parameter regression coefficients were compared for the two models. Based on Byrne's (2001) recommendation, a critical ratio of 1.96 or higher will indicate a significant difference between the models at the 0.05 level. Hence, our result lends confirmation to the initial finding that employment status strengthens the positive influence of RAW on RUE that indicating that entry-level employees ($\gamma = 0.341$, $p < 0.001$) tend to associate robots with unemployment than their higher-level counterparts ($\gamma = 0.455$, $p < 0.001$) (See Fig. 2).

Similarly, our result ($\gamma = .206$, $p < .001$) indicated that employment status dampens the positive relationship between SSOR and RUE that indicating that the higher you go on the employment ladder, the less you associate the social skills of robots with robot-induced unemployment (see Fig. 3). Fig. 4.

3. Discussion and conclusion

Over the decade, robots have perceived a histrionic growth, but there are still several robotic use restrictions in the job sectors. Especially in the hospitality and tourism industry, human service is still the heart of products and experiences. Subsequently, the service robotic success or failure depends on the manufacture and installed algorithms. So robotic service's main disadvantages could be service failure and mechanical error, high cost of maintenance, and return on investment. Besides, a continuously updated version is coming, so with the new factories' customers' demands will change, so it will not be easy to replace, update, or modify (Horwitz, 2020) like human employees can be skilled through training.

Technology, sustainability, and management vision determine the critical success factor in future travel, tourism, and hospitality. In the rapidly changing situation, the tourism industry needs to continuously acclimate robots to customers' demands and be sustained in the competitive business environment. Moreover, at this moment, the situation requires the use of robots for service (food and drinks), sanitization (killing germs and viruses), and information guidance (Chatbots, robot assistants). Finally, the hospitality and tourism industry should regard robots as a prime concern to overcome after the coronavirus situation to re-establish the image of the tourism industry. Besides, service robots could allow employees to be more skillful and work at the operator level. This new trend may establish a new identity in the hospitality and tourism industry and accomplish long-term success and sustainability.

Table 5
Result of hypotheses testing.

	Relationships	Std. Beta	Std. Error	T-values	P-values	2.5%	*97.5%*	Decision	VIF	R^2	Q^2
H1	RAT → Robot induced unemployment	0.070	0.051	1.187	0.236	-0.030	0.172	Not-supported	1.244		
H2	REX → Robot induced unemployment	0.050	0.056	0.826	0.409	-0.059	0.164	Not-supported	1.441		
H3	SSOR → Robot induced unemployment	0.229	0.051	4.600	0.000	0.133	0.336	Supported	1.393		
H4	RAW → Robot induced unemployment	0.449	0.044	10.120	0.000	0.360	0.532	Supported	1.155		
H5	Work status*SSOR → Robot induced unemployment	-0.080	0.047	-1.978	0.055	-0.151	-0.013	Supported			
H5	Work status*RAW → Robot induced unemployment	0.091	0.042	2.151	0.031	0.014	0.160	Supported			
	Robot induced unemployment									0.361	0.249

Note: *** $p < 0.001$, **$p < 0.05$, Perceived Advantage of Robots = RAT, Previous Experience with Robots = REX, Social Skills of Robot = SSOR, Robot Awareness = RAW,

Table 6
Testing moderating effect of employment status.

Path in the unconstrained model	Entry/Skilled level	Managerial Level	Critical ratio for the difference between parameters	Path significance between unconstrained and constrained models			Hypothesis
	Estimate (CR)	Estimate (CR)		χ2	df	Δχ2	
Unconstrained model				359.449	120	–	
Fully constrained model				388.139	132	28.69**	Supported
RAT Robot→-induced unemployment	0.127(1.356)	0.112(1.170)	1.42	359.619	122	0.17	Not-supported
REX Robot→-induced unemployment	0.048(0.451)	0.034(0.356)	1.56	360.129	122	0.68	Not-supported
SSOR Robot→-induced unemployment	0.206(2.112)	0.188(1.987)	2.89**	365.239	122	5.79**	Supported
RAW Robot→-induced unemployment	0.341(4.032)	0.455(4.732)	3.07**	369.099	122	9.65**	Supported

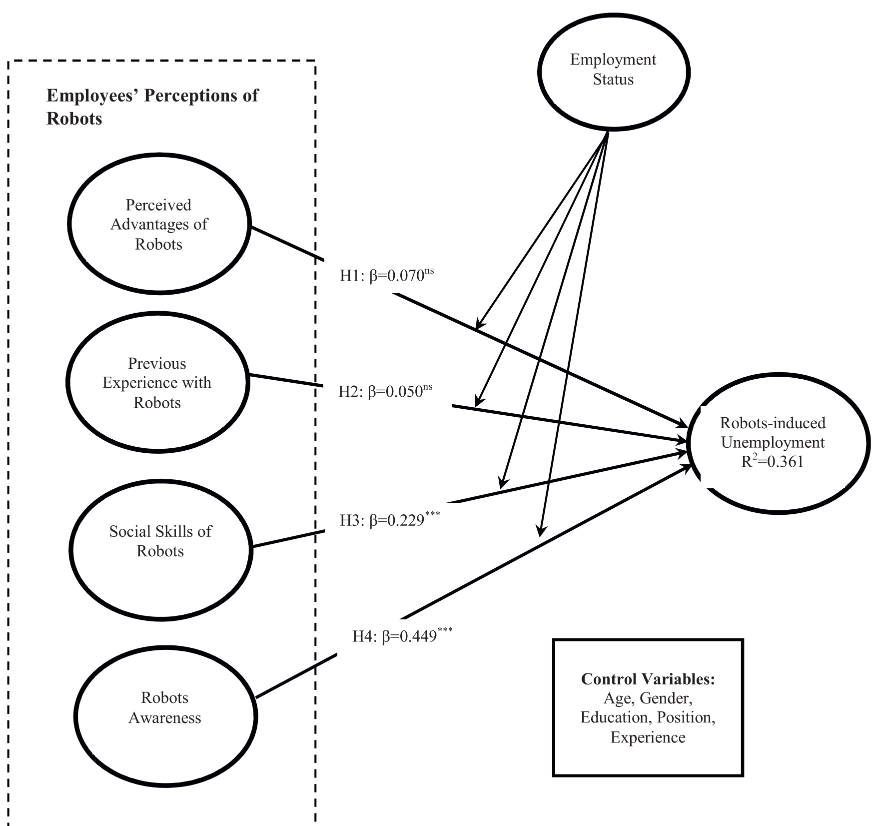

Fig. 2. Model with the results.

3.1. Theoretical implications

This study contributes new theoretical implications to the literature in the hospitality service regarding employees' perception of robots and robots induced unemployment. This study set out a research outline by adopting a combination of employees' observations on service robots and robots encouraging unemployment. Recently after the COVID-19 effect, service robots' adoption has engaged the perception of employees (Van Looy, 2020; Vatan and Dogan, 2021), consumers (Zhong et al., 2020; Lu et al., 2019), and technological evolutions (Zeng et al., 2020; Wang and Wang, 2021). The central theoretical contribution of this study is the illustration of a literature-based investigation of service robots for the organizational decision-making on service robots' adoption practices in the tourism and hospitality industry.

Wang and Wang (2021) advocate a systematic literature survey of the robotic technologies during the COVID-19 pandemic. Van Looy, September) (2020) researched adding Intelligent Robots to Business Processes and Analyzing the employees' perceptions. Similarly, Vatan, and Dogan (2021), did a qualitative study in Turkey on hotel employees' thoughts about service robots' adoption. The current research offers a significant framework for tourism and hospitality researchers and related authorities that associate current service robots' research trends. This framework improves the theoretical foundations of robotic acceptance and service robots' adoption intensities and encourages a complete research direction. Although service robots' adoption inside the tourism and hospitality industry covers several issues for organizational decision-making, several issues still need to be worked. Our study fulfills this gap by consolidating the current research agenda. Besides, the findings of this study offer innovative theoretical understanding by presenting employees' perception impacts on commercial decision-making consequences among guest service departments, human resource management, marketing, and finance.

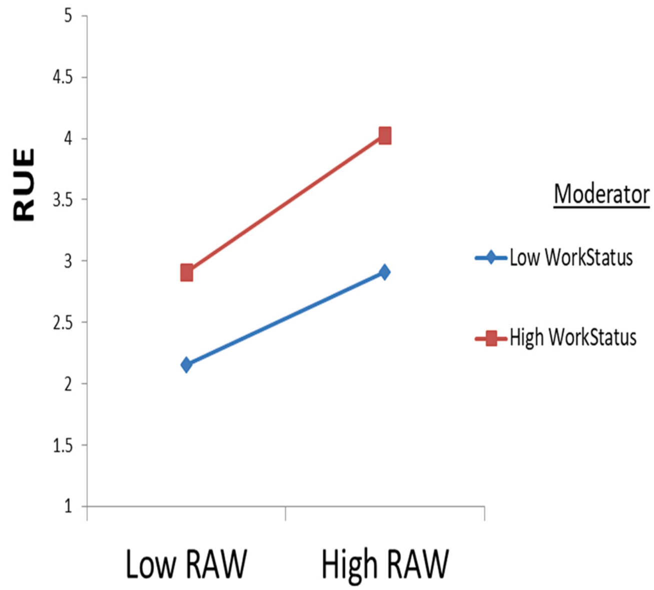

Fig. 3. Interaction effect of Work status in the relationship between RUE and RAW.

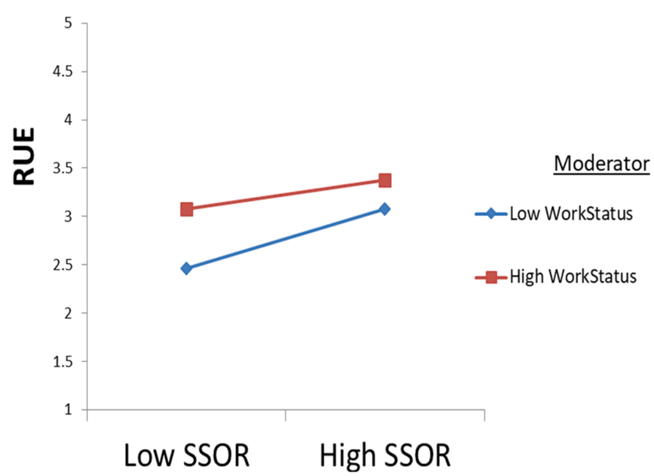

Fig. 4. Interaction effect of Work status in the relationship between RUE and SSOR.

3.2. Managerial implications

Along with COVID-19 technological expansion has diverted the mindset of customers, employees, and management. Due to the effectiveness and enlargement in numerous service sectors, tourism, and hospitality sectors, managers focus on considering the customers' demand for service robots and employees' intention toward robots in their organizations (Lin et al., 2021; Kim et al., 2021; Horwitz, 2020). To the extent that mechanical objects such as artificial intelligence, machine learning, and virtual reality, Chatbots accomplish a task more accurately and in comparison with human counterparts' robotic devices do cost lower in sophisticated frontline tasks (Brougham and Haar, 2018; Ukpabi et al., 2019; Ivanov et al., 2020). However, successful customer support is crucial to assure this innovation for the medium and long term. The findings of this study propose that employees' perception of service robots not only concerns themselves with benefits but also be aware of future unemployment and intend to turnover (Li et al., 2019) or pay attention to advance level of qualifications and technical skills, but robots' adoption has a clear advantage for consumers in terms of service enrichment.

Managers should be aware of the implications of these research findings, which indicate that lower-skilled positions involving routine business service functions are likely to be replaced by robots. Managers may consider establishing and executing training programs to assist people in improving skills to lessen unfavorable perceptions of robots within their workforce. While the engineers work on improving the social skills of robots to enhance guest satisfaction, employees can develop their abilities to perform more creative and innovative service offerings for guests and managers.

In the broad picture, robots' adoption in the tourism and hospitality industry is beneficial for both employees (reduced extra workload, speed up the tasks) and customers (avoiding poor service quality, receiving service on time). Therefore, service robots' adoption would not negatively influence service quality, but service experience would be different in traditional service establishments by frontline employees. Incidentally, our study displays that employees' perceptions of robots and customers' intention to use them are highly based on their ascriptions. Therefore, management should ensure that adopting service robots is not harmful but optimistic and experience a new way of service at critical and regular times. Existing literature on robot awareness, perception acceptance, and adoption considers robots a threat to employment and inhospitable for some customers. Our study concludes the findings and suggests that managers emphasize employee motivation, specifically entry-level, and introduce robots as high levels of fantasy to customers.

3.3. Limitations and future research

Regardless of the remarkable contributions, this study has a few limitations that suggest further research prospects. Because the nature of the methodology engaged requires few restraints worth revealing. Even though several types of research have established that robots perceive advantage, perceived disadvantage, perceived awareness, intention to use, and actual use are usually highly correlated in the perception of robots. At first, it was not possible to collect data from travel and tourism organizations because of the COVID-19 spread out. Therefore, the data of this study was collected from MTurk (USA). Therefore, future research could collect data directly from the organizations. Also, only English-speaking employees were considered. Moreover, many participants did not mention their current work conditions and situations, which could also be measured as a study limitation. In this research, we did not differentiate the level of employment, so entry-level, skill-level, and supervisor-level employees' responses could not separate. In this regard, future studies may consider the job level and separately identify their intention toward service robots in their organization.

Data availability

Data will be made available on request.

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