To cite this article: Stephanie Hui-Wen Chuah, Eugene Cheng-Xi Aw & Cheng-Feng Cheng (2021): A silver lining in the COVID-19 cloud: examining customers' value perceptions, willingness to use and pay more for robotic restaurants, Journal of Hospitality Marketing & Management, DOI: 10.1080/19368623.2021.1926038

To link to this article: https://doi.org/10.1080/19368623.2021.1926038

A silver lining in the COVID-19 cloud: examining customers' value perceptions, willingness to use and pay more for robotic restaurants

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ABSTRACT

The COVID-19 pandemic has severely affected the restaurant industry due to enforced closures and limitations on social gatherings, prompting restaurateurs to innovate and adapt in order to ensure the viability of their businesses. Pandemic has also induced changes in our perceptions of safety in public spaces, necessitating the adoption of social distancing and more widespread use of online platforms for purchasing and communication. While the pandemic might be a catalyst for the adoption of contactless technologies, some restaurateurs remain hesitant to invest in service robots because they are not convinced of the return on investment and the potential value service robots can deliver to their customers. Therefore, this study aims to explore customer value perceptions of service robots and their impact on customers' attitudes and behaviors toward robotic restaurants. Findings yielded by a survey of 445 potential diners in Taiwan show that customers' willingness to use and to pay more for robotic restaurants are determined by their attitudes toward robots, which are influenced by functional, conditional, epistemic, emotional, co-creation, and social values. Our survey results also reveal that the importance of conditional value is amplified by crisis-specific antecedents, namely the need for physical distancing and mysophobia. These findings have implications for restaurant pricing policies and can be considered by restaurant managers when formulating strategies aimed at sustaining their business in these challenging times.

由于强制关闭和限制社交聚会, COVID-19大流行严重影响了餐饮业, 促使餐馆经营者进行创新和调整, 以确保其业务的生存能力. 流感大流行还导致我们对公共场所安全的看法发生了变化, 这就需要采用社交距离, 并更广泛地使用在线购物和交流平台. 虽然这种流行病可能是采用非接触式技术的催化剂, 但一些餐馆老板仍然对投资服务机器人犹豫不决, 因为他们不相信服务机器人能给顾客带来的投资回报和潜在价值. 因此, 本研究旨在探讨顾客对服务机器人的价值认知及其对顾客对机器人餐厅态度与行为的影响. 对台湾445位潜在食客的调查结果显示, 顾客对机器人餐厅的态度决定了他们对机器人餐厅的使用意愿和支付意愿, 这些态度受到功能、条件、认知、情感、共同创造和社会价值观的影响. 我们的调查结果还显示, 条件价值的重要性被特定危机的前因放大, 即需要身体距离和神秘恐惧症. 这些发现对餐厅定价政策有一定的启示, 可供餐厅经理在制定策略时加以考虑, 以期在这个充满挑战的时代维持其业务.

KEYWORDS

COVID-19; service robots; customer perceived value; physical distancing; mysophobia; willingness to pay more

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Introduction

In the last year, the coronavirus (COVID-19) pandemic has altered people's lives, wreaked havoc on the global economy, and brought restaurant operations to a shuddering halt. Many restaurants have been forced to temporarily shut down or limit their operations to only takeaway and online orders due to government-imposed lockdowns or tight restric- tions on movement to stem the spread of infection (Gursoy & Chi, 2020). Since the World Health Organization (WHO) declared COVID-19 as a pandemic on March 11th, 2020, most restaurants have been running at 10−20% below the previous years' capacity (Dube et al., 2020). Given that this mode of operations was inadequate to cover all operating costs, nearly 10,000 restaurants in the U.S. were closed within six months following the first shutdown, leaving 3 million employees out of work (National Restaurant Association, 2020). By the end of 2020, total restaurant and food-service sales in the U.S. were 240 USD billion lower than the pre-pandemic forecast of 899 USD billion (National Restaurant Association, 2021).

While some countries have begun lifting restrictions on indoor dining, most restaurateurs are facing labor shortages and a severe reduction in the number of dine-in customers due to consumers' fear of virus transmission by employees and other patrons (ET Retail, 2020). Aware of these issues, upon resuming operations, many restaurants have reestablished their health and safety protocols to alleviate the risk of coronavirus infection and motivate customers to come back (Seyitoğlu & Ivanov, 2020a). These precautions include checking the body temperature of staff and customers, putting sanitizing hand rub dispensers, regularly cleaning and disinfecting high-touch surfaces (e.g., tables and menus), using small baskets to exchange payments, and spacing out tables to comply with the social distancing guidelines. From plastic partitions to igloos, restau- rants have come up with different creative solutions to help with physical distancing among customers. The owners of Amsterdam's Mediamatic restaurant have installed small glass houses that surround each table, whereby waiters wearing face shields are using long boards to bring dishes to diners without entering the enclosures (Liubchenkova, 2020). While masks, gloves, and protective gear will add a layer of protection against the spread of coronavirus, many restaurateurs are still struggling to make their kitchens completely safe. According to public health experts, the cramped and crowded kitchen conditions will increase the likelihood of infection transmission among employees. Furthermore, masks can easily slip down and get contaminated in hot environments (Haddon & Maidenberg, 2020). The impact of infectious disease can be devastating for businesses that have just started to welcome dine-in guests again. The dangers that restaurants are still facing are exemplified by the Fremont Brewing restau- rant in Seattle that was forced to shut down indefinitely after an employee tested positive for COVID-19 only 10 days after reopening the patio for diners (Guarente, 2020).

Just as other businesses have found ways to accommodate various COVID-19-related restrictions, restaurant owners are starting to embrace technology, shifting the industry from high-touch to high-tech (Zeng et al., 2020). Among the innovations that have been introduced, service robots have made the greatest impact, given that they are "system based autonomous and adaptable interfaces that interact, communicate and deliver service to an organization's customers" (Wirtz et al., 2018, p. 909). Because robots are immune to viruses, robot chefs and waiters have become an ideal option for reducing human contact and enhancing food safety and sanitation (Lu et al., 2021; Seyitoğlu & Ivanov, 2020b). Even before the pandemic, many restaurant and café chains (e.g., Caliburger, Haidilao, and Dal. komm) were utilizing robots to save costs and enhance operational efficiency. A Mckinsey study revealed that labor costs have more than doubled in the past 30 years, while the average robot price has declined by half in real terms (Tilley, 2017). In China, labor costs in the catering industry increased by 24.4% percent in 2019 in year-on-year terms, surpassing all other operating costs (Xinhua, 2020). Thus, it is not surprising that robots are seen as an effective cost-saving strategy for restaurants. Indeed, according to Ren (2020) China's biggest hotpot chain Haidilao has managed to save 172,000 yuan monthly by replacing its human staff with service robots.

While contactless technologies will become part of the new normal, some restaurateurs remain hesitant to invest in service robots because they are not convinced that such investments are financially worthwhile (Mathath & Fernando, 2015). One possible way to allay this concern is increasing prices to compensate for the additional costs. However, empirical evidence regarding customers' willingness to pay more for robotic services is scant. Like any other technological innovation, the long-term viability of a robotic restaurant depends on its ability to deliver superior value to customers, ultimately improving loyalty and profitability (De Kervenoael et al., 2020; Zhang et al., 2020). Value is created when customers' perceptions of benefits acquired from the consumption of a product/service exceed the costs incurred (Christopher, 1996). While the COVID-19 pandemic has reshaped consumers' expectations and the way businesses operate, most robotic research in the tourism and hospitality industry was conducted before the crisis (e.g., Cha, 2020; De Kervenoael et al., 2020; Zemke et al., 2020). Moreover, a holistic understanding of how customers perceive the value of service robots is lacking because authors of previous studies tended to conceptualize customer value as a unidimensional construct or a simple trade-off between benefits and sacrifices (e.g., Cha, 2020; De Kervenoael et al., 2020). According to Sheth et al. (1991), customer perceived value is a complex and multifaceted construct, comprising of functional, emotional, social, epistemic, and conditional aspects. Notably, conditional value refers to the utility derived from an alternative (e.g., robot-delivered versus human-delivered services) when consumers are confronted with critical situations (Sheth et al., 1991). As a special case construct, conditional value has received much less attention in the tourism and hospitality studies (e.g., Ha & Jang, 2012; Jiang & Kim, 2015). Since the onset of the COVID-19 pandemic, physical distancing and mask wearing have become the norm in most societies, as people have become more worried about personal hygiene (Seyitoğlu & Ivanov, 2020a; Wen et al., 2020). However, little is known about the crisis-related factors that influence the conditional value of service robots. Furthermore, notwithstanding the collaborative capabilities of service robots, the understanding of their role in mediating customer experience co-creation remains limited (Murphy et al., 2019; Severinson-Eklundh et al., 2003). These gaps in the pertinent literature have motivated the present study, guided by the following research questions:

RQ1: What drives customers' willingness to use and to pay more for robotic restaurants?

RQ2: How do the value perceptions of service robots influence customers' attitudes and behavioral intentions?

RQ3: How do crisis-specific factors, such as the need for physical distancing and mysophobia (fear of contamination), affect the conditional value of service robots?

Providing answers to these questions will contribute to the extant body of literature in three ways. First, unlike previous studies that merely focus on a single outcome variable such as acceptance and intention to use (e.g., Cha, 2020; De Kervenoael et al., 2020; Wirtz et al., 2018), this investigation shows that customer attitudes influence not only their willingness to use but also their willingness to pay more for robotic restaurants. We thus heed the recent call made by Seyitoğlu and Ivanov (2020a) for empirical research focusing specifically on customers' willingness to pay more for robot-delivered services. As Kuo et al. (2017) asserted, "the assessment of cost and profit modes and new innovativeness services with new technology must be financially calculated before the implementation" (p. 1307). The findings yielded by the present study also reveal that customers' willingness to use and to pay more for robotic restaurants are determined by their attitudes, which are influenced by functional, conditional, epistemic, emotional, co-creation, and social values. Second, this study extends the theory of consumption values (Sheth et al., 1991) by incorporating two crisis-specific factors as the antecedents to conditional value. Although physical distancing is an important safety protocol that service businesses must adhere to in these challenging times, this construct has seldom been studied in the service domain (Khoa et al., 2020; Sigala, 2020). Furthermore, even though the COVID-19 pandemic has triggered fear and anxiety in many individuals, the psychological consequences of this crisis have not been sufficiently explored in academic research (Hassan & Soliman, 2020). Thus, by examining the need for physical distancing and mysophobia, this study responds to Gursoy and Chi (2020) call for urgent behavioral and causal research aiming to elucidate consumers' health-protective behavior and their mental well-being. Lastly, by adopting the service-dominant logic (SDL) lens, this investigation is among the initial attempts to empirically validate the role of co-creation value in artificial intelligence (AI) and robotics research, thus enriching the theory of consumption values. Its findings also provide some important implications for restaurant pricing policies, and help managers better cope with the challenges posed by the COVID-19 crisis.

Literature review

Robots in the service industry

The development of robots is one of the most groundbreaking technological innovations that have taken place within the service industry in recent years (Chuah & Yu, 2021). Fueled by recent advances in mechanical engineering and AI technologies, robots have moved out of the factories and are increasingly being integrated into service delivery operations (Čaić et al., 2019). Holding the promise of improving productivity and cost efficiency, robots have gained traction in healthcare, education, tourism, and hospitality industries (Hwang et al., 2020; Tung & Au, 2018). A service robot is defined as "one that autonomously performs useful tasks for humans or equipment outside an industrial automation application without human intervention" (Zemke et al., 2020, p. 3). In fact, most robots adopted in the tourism and hospitality industries were initially aimed at the manufacturing sector and were later modified to suit the requirements of travel-related services, giving rise to baggage-handling robots (previously employed as material-handling robots), housekeeping robots (previously used as industrial cleaning robots), and robotic barista arms with coffee- or cocktail-maker functions (formerly deployed in robotic manufacturing assembly lines) (Zemke et al., 2020).

Owing to labor shortages coupled with rising labor costs, restaurateurs have started to embrace automation technologies (Cha, 2020). Automated restaurants, also known as robotic restaurants, leverage robots to perform specific tasks (Hwang et al., 2020). Depending on their technological features, some robots can take orders, prepare meals, and deliver them to customers, whereas others can sing or dance to entertain customers (Seyitoğlu & Ivanov, 2020c). For example, in the U.S., Spyce created the world's first robotic kitchen that can dispense up to 210 meals per hour (Wolfe, 2018). In Japan, tech giant Softbank opened Pepper Parlor Café, where robotic staff take orders and make dessert recommendations based on customers' facial expressions (Robotics Research, 2019). In Hajime robot restaurant in Thailand, Samurai robot waiters not only deliver food and clean tables, but also perform dance stylings for customers. While many restaurateurs have already recognized robots' potential for cost savings and service quality improvements, not all tasks are deemed suitable for robotization (Seyitoğlu & Ivanov, 2020c). Ivanov and Webster (2019) assessed customer perceptions toward the robotization of various tourism-related activities using a global sample of over 1,000 respondents. Their findings indicated that providing information about the menu, taking orders, and cleaning tables were considered as more acceptable and appropriate robotic functions compared to cooking and serving food.

In the midst of the COVID-19 pandemic, robots are seen as "heroes" by many due to their ability to handle perilous tasks, such as disinfecting hospital rooms, delivering meals or medicine to patients in quarantine, and transporting infectious samples for laboratory testing. Their utilization can minimize interpersonal contact and reduce the chance of health workers contracting infection from patients or object surfaces in hospitals (Bogue, 2020). Robots are also deployed to measure body temperature, or to remind people to wear masks and keep physical distance in public spaces (Seyitoğlu & Ivanov, 2020b). Likewise, there has been a surge in demand for robot companions amidst COVID-19 pandemic as lockdowns have exacerbated problems of isolation, particularly for people in senior living facilities (Lever & Jammot, 2021).

The impact of COVID-19 on consumer behavior

The COVID-19 pandemic has changed the way consumers behave and has disrupted the retail landscape. Some enforcements have been sudden and involuntary, such as man- datory mask wearing, social distancing, travel restrictions, and prohibition of mass gatherings, to name a few. As the pandemic has persisted for more than a year, consumers have learned to improvise and have adopted new habits. For example, due to complete lockdown in some countries, consumers are unable to shop at the grocery stores and have started ordering their products online (Sheth, 2020). The immediate impact of COVID-19 on the retail industry has been profound, but its long-term effects are yet to be determined (Roggeveen & Sethuraman, 2020). The fear and uncertainty surrounding COVID-19 have triggered panic buying, such as hoarding toilet paper, instant noodles, and canned food in order to be prepared for an indefinite quarantine (Laato et al., 2020; Sheth, 2020). Consequently, retailers have seen a surge in demand for essential household items, while facing challenges with managing inventory, supply chains, and delivery (Roggeveen & Sethuraman, 2020). Puttaiah et al. (2020) have outlined five key trends in the behavioral changes amid COVID-19: (1) Increased digital adoption. People are shifting to digital platforms for working, learning, and entertain- ment. Many households with access to internet have learned to participate in Zoom meetings to stay connected with family members and friends (Sheth, 2020); (2) Changes in mobility patterns. People are increasingly working, studying, and spending leisure time at home, thus blurring the work−life boundaries (Sheth, 2020). There is also an emerging aversion for public transport and high-density transit hubs (Fabius et al., 2020); (3) Changes in purchasing behaviors. Consumers may choose value-based pur- chasing and shop online; (4) Increased awareness of the importance of health and wellness. People are adopting healthier lifestyles (e.g., eating healthily and taking plenty of exercise) to boost their immune systems; (5) Changes in interpersonal behavior. Due to severe restrictions on mobility, most individuals spend majority of their time at home, resulting in a spike in divorce rates and a rise in pet adoption. It is expected that some of these trends will be reversed once the pandemic ends. However, it is also possible that consumers will discover more affordable, accessible, and convenient ways of doing things that have previously required visiting public spaces or human interaction. For example, consumers may become accustomed to online fitness classes and streaming services (e.g., Netflix and Disney). As a result, they will be less likely to return to gyms and movie theaters even when the pandemic is over (Sheth, 2020).

Before the pandemic, hoteliers were skeptical about the use of service robots since human touch is considered a core competency in the hotel industry (Y. Choi et al., 2020b). For example, interviews conducted by Ivanov et al. (2020) with Bulgarian hotel managers revealed their wariness of deterioration in service quality as a result of robot deployment. The managers maintained that skilled and well-trained human employees were valuable assets that could not be fully replaced by robots (Ivanov et al., 2020). Similar attitudes were uncovered by Seyitoğlu and Ivanov (2020c) by analyzing the TripAdvisor reviews. The travelers that contributed to this platform opined that robots were not competent enough to replace human waiters in restaurants because they can only serve certain menu items and may cause service failures due to incorrectly processing orders or bringing food to wrong tables. In their study, Y. Choi et al. (2020b) carried out an experiment in a hotel context to compare guest perceptions of the service provided by human staff, service robots, and a combination of both. These authors found that human staff were preferred by the customers and outperformed service robots with respect to interaction quality and physical service environment. In examining the impact of robotic services on brand experience, Chan and Tung (2019) found that hotel guests perceived higher levels of sensory and intellectual experience from robotic services, but lower levels of affective experience com- pared to human staff. As Rigie (2018) pointed out, consumers may have different expecta- tions toward robots since they are designed to deliver futuristic service experience rather than providing the level of hospitality a human staff member can offer. Owing to the rapid development of AI technologies, these robots are expected to emulate humans with much greater fidelity, and will be able to exhibit hospitality skills such as being courteous and helpful. During the pandemic, Kim et al. (2021) observed that travelers were highly concerned about the risk of infection when staying in human-serviced hotels due to high levels of interpersonal contact. Therefore, many were willing to explore safer options, such as robot-staffed hotels.

The COVID-19 pandemic has also revolutionized the way restaurants operate, giving rise to the contactless dining experience (Pendrill, 2020). While the future is unpredictable for most restaurants, consumers have clear expectations about the steps that need to be taken to make their food ordering and indoor dining safe. According to a recent study conducted by Datassential (2020a), 81% of surveyed customers stated that contactless ordering would make them feel safer when dining out, while 82% of the respondents stated the same regarding payments. Notably, 46% of the surveyed individuals indicated that low- or no-contact food preparation was the most important contactless experience at restaurants (Datassential, 2020b). Even though consumers are growing more comfortable with the use of AI and robotic technologies, as confirmed by Interactions LLC's (2020) survey of 1,000 people across the U.S., the COVID-19 upheaval has brought new prospects and applications for robots (Zeng et al., 2020), as many restaurants have been forced to invest in automation and robotics as a means of providing more hygienic and contactless dining experience to ensure their survival.

The multidimensional perspective of customer value

As the key foundation for all marketing activities, customer perceived value continues to receive considerable attention in the marketing literature (Holbrook, 1994). Creating superior customer value has long been recognized as the key source of competitive advantage, as it is the desired end-goal of every consumption situation (Ha & Jang, 2012; Woodruff, 1997). One of the most widely cited definitions of customer value is provided by Zeithaml (1988), who described it as "the customer's overall assessment of the utility of a product based on perceptions of what is received and what is given" (p. 14). This definition, however, considers value as a unidimensional construct, equating it to a mere cognitive trade-off between benefits and costs, typically quality versus price (Sánchez-Fernández & Iniesta-Bonillo, 2007). This unidimensional view has been criticized by many scholars for its over-simplicity, given that it fails to capture the complex and multidimensional nature of customer value, which includes socio- psychological aspects as well (Teng & Chang, 2013; Williams & Soutar, 2009). For example, Babin et al. (1994) identified two types of shopping value – utilitarian value which denotes task-, functional-, and rational-related benefits, and hedonic value that reflects entertainment and emotional worth. In an earlier study, Sheth et al. (1991) developed the theory of consumption values to better understand consumer choice behavior. Their model, which has been widely adopted in the tourism and hospitality literature (e.g., Ha & Jang, 2012; Jiang & Kim, 2015; Williams & Soutar, 2009), conceptualizes customer value according to five dimensions, denoted as functional, emotional, social, epistemic, and conditional values. Drawing on the aforementioned theory, Sweeney and Soutar (2001) proposed the PERVAL framework for use in the context of durable goods. They classified customer value as functional-quality value, functional-price value, emotional value, and social value. The present study was underpinned by the theory of consumption values, which includes epistemic and conditional values. This choice was deemed appropriate since service robots are novel innovations, and the COVID-19 crisis has necessitated their deployment in containing the spread of coronavirus.

Functional value

Functional value denotes the useful, practical, and utilitarian value, i.e., something that helps accomplish a certain task (J. Choi et al., 2020a). In the case of service robots, it represents how well they perform their intended function (Zhang et al., 2020). Empowered by technology-mediated learning, smart technologies such as AI and robotics can substitute or complement frontline employees' efforts to boost service efficiency and effectiveness (Marinova et al., 2017). Unlike human employees, service robots have the ability to work 24/7 and can perform tasks with greater speed and accuracy. They can also repeat the same tasks without getting bored or losing focus (Ivanov et al., 2020). Currently, robots are used in restaurants to prepare meals with high degree of consistency and carry out multiple tasks, such as scrubbing dishes, keeping the kitchen clean, and serving food to customers (Joshi, 2020). Thus, their deployment can enhance both productivity and service quality. Within the hospitality industry, De Kervenoael et al. (2020) found that perceived usefulness increased the value of social robots, which in turn influenced visitors' behavioral intentions. Thus, we propose that:

H1: *Functional value has a positive effect on customers' attitudes toward robotic restaurants.*

Emotional value

Emotional value refers to the positive feelings or affective states elicited during an interaction with a product or service (Sheth et al., 1991). Examples of emotional value include fun, pleasure, joy, enjoyment, entertainment, and excitement (Lu et al., 2019; Zhang et al., 2020). With the aid of human−robot interaction systems that incorporate facial expression recognition, service robots can convey affective responses to users by interpreting their facial expressions, processing their emotions, and stimulating their feelings (Tung & Au, 2018). In particular, humanoid robots can offer fun experience for small kids (Joshi, 2020). Findings yielded by previous studies in this domain indicate that hedonic motivation not only influences customers' evaluations of the performance and effort expectancies of AI-based robotic devices, but also affects their emotions toward these devices (e.g., Gursoy et al., 2019; Lin et al., 2020). In addition, Cha (2020) confirmed that, the greater the hedonically motivated consumer innova- tiveness, the more positive the customers' attitudes toward robot-serviced restaurants. Thus, we posit that:

H2: *Emotional value has a positive effect on customers' attitudes toward robotic restaurants.*

Social value

As a product can function as a symbolic communication tool, it fulfills the human need for social status, prestige, and recognition in the reference group (Eastman et al., 1999; Grubb & Grathwohl, 1967). Social value is the utility acquired from the ability of a product or service to enhance social self-concept (Sweeney & Soutar, 2001). This argument is grounded in the theories of impression management (Goffman, 1959), which suggest that the creation of a favorable social image is the internal driving force for consumer purchases (Shukla, 2012). Prior research has highlighted the importance of social motivation in new technology adoption. For example, Hwang et al. (2019) found that people use drone food delivery services to impress and differentiate themselves from others. More recently, Cha (2020) determined that socially motivated consumer innovativeness was significantly correlated with attitudes toward robotic restaurants. Thus, we hypothesize:

H3: *Social value has a positive effect on customers' attitudes toward robotic restaurants.*

Epistemic value

Epistemic value arises from the ability of a product or service to spark curiosity, generate novelty, and/or satisfy user's quest for knowledge (Sheth et al., 1991). As people rarely encounter service robots in their current daily life, they enjoy the novel and interesting experience of meeting, talking, and interacting with service robots (Belanche et al., 2020; Sheth et al., 1991). In their analysis of online reviews consumers provided on multiple travel websites, Tung and Au (2018) found that hotel customers described such experiences using terms like "wow," "surprise," and "novel." Thus, the authors argued that using service robots for food preparation and delivery is some- thing new that can trigger restaurant customers' curiosity, thereby fulfilling their psychological need for novelty (Tung & Au, 2018). It is a well-known fact that customers who are highly curious and prone to novelty-seeking tend to have more favorable attitudes toward using new technologies (Adapa et al., 2020; Dabholkar & Bagozzi, 2002). Thus, we propose that:

H4: *Epistemic value has a positive effect on customers' attitudes toward robotic restaurants.*

Co-creation value

The concept of co-creation has its roots in service-dominant logic (SDL), which places services, rather than products, at the core of economic exchange (Vargo & Lusch, 2004). Exchange of services occurs when at least two parties contribute to the value creation process by sharing knowledge and resources (Mathis et al., 2016). Prahalad and Ramaswamy (2004) described co-creation as the "joint creation of value by the company and the customer, allowing the customer to co-construct the service experi- ence to suit her context" (p. 8). According to the SDL, rather than being passive recipients of value, customers are increasingly viewed as proactive co-creators. Correspondingly, the role of companies has been transformed from being producers of standardized value to facilitators of the value co-creation process (Chan et al., 2010). Because of their direct contact with customers, frontline employees play an essential role in facilitating co-creation activities (Campos et al., 2018). Through this collabora- tive interaction, value is added and mutually beneficial outcomes are produced (Mathis et al., 2016).

As the COVID-19 pandemic has precipitated the use of service robots, it is expected that these robots will replace frontline employees and will alter the way value is co- created and experienced (Kaartemo & Helkkula, 2018; Thomas, 2020). Owing to their increasingly advanced social functionalities, service robots are capable of mimicking the interactions human employees have with their customers (Čaić et al., 2019). Although people typically look for human elements in their interactions, Tung and Au (2018) showed that hotel guests can co-create unique experiences by interacting with robots. Their findings further revealed that, while some hotel guests proactively look out for service delivered by robots, others treat robots as companions and converse with them in order to build deeper human−robot relationships. In the cultural heritage place domain, Jung and Tom Dieck (2017) illustrated the importance of cutting-edge technologies (e.g., augmented/virtual reality and 3D printing) in co- constructing rich and memorable experiences (Tung & Au, 2018). Furthermore, Mathis et al. (2016) demonstrated that co-creation value positively influenced tourists' vacation experiences and loyalty. On this basis, we postulate that consumer recognition of the robots' potential to co-create personalized dining experiences can lead to more favorable attitudes, giving rise to the following hypothesis:

H5: *Co-creation value has a positive effect on customers' attitudes toward robotic restaurants.*

Conditional value

Conditional value is generated under certain circumstances depending on time, location, the social and technological contexts, or the consumers' mental state (Pihlström & Brush, 2008). It offers ephemeral and substantial value to consumers in particular seasons or when they are faced with emergency situations and other events that may occur only once in a lifetime (Pura, 2005). For example, face masks and hand sanitizers play a particularly salient role in combating coronavirus during the COVID-19 pan- demic. Since the onset of the pandemic, robots have been adopted to perform a wide variety of tasks to keep people safe. For example, robots are now utilized to disinfect hospitals, take people's temperature, as well as deliver food and medicine to patients (Davis, 2020). Thus, it is reasonable to assume that the unprecedented circumstances imposed by the COVID-19 crisis will augment the conditional value of robots in the eyes of consumers, leading to the development of favorable attitudes as reflected in the following hypothesis:

H6: *Conditional value has a positive effect on customers' attitudes toward robotic restaurants.*

Need for physical distancing

In response to the COVID-19 outbreak, the WHO offered some guidelines to prevent the spread of infection. One of the most common preventive measures is physical distancing, which represents the "efforts that aim . . . to decrease or interrupt transmission of COVID-19 in a population (sub-)group by minimizing physical contact between potentially infected individuals and healthy individuals, or between population groups with high rates of transmission and population groups with no or a low level of transmission" (ECDC, 2020, p. 2). Various physical distancing measures have been imposed at the individual (e.g., keeping at least 6 feet apart from others, self-isolation, and quarantine) and societal (e.g., closures of schools/workplaces and cancelations of mass gatherings) level (ECDC, 2020).

From mannequins and individual greenhouses to service robots, restaurants have adopted creative ways to enforce physical distancing. For example, a café in Daejeon, South Korea, is using robotic baristas to prepare drinks and deliver them to customers. The barista system can also transmit data to other devices, communicate with customers, and make use of self-driving technology to find the best route around the café (Shin, 2020). Thus, we expect that the need for physical distancing will increase the conditional value of service robots and therefore hypothesize:

H7: *The need for physical distancing has a positive effect on the conditional value of service robots.*

Mysophobia

The COVID-19 pandemic may usher in a wave of mysophobia as people are constantly reminded to wash their hands frequently and to disinfect high-touch surfaces (Scott, 2020). Mysophobia, also known as germaphobia, is an irrational fear of contamination or germs. The term was first introduced by William A. Hammond in 1879 in reference to the excessive handwashing as a symptom of obsessive-compulsive disorder (OCD). According to the National Institute of Mental Health (2019), OCD is a common, chronic and long-lasting disorder in which a person has uncontrollable, reoccurring thoughts (obsessions) and/or behaviors (compulsions) that he or she feels the urge to repeat over and over. Clinical health psychologists have observed the exacerbation of preexisting fears of germs among OCD patients during the COVID-19 pandemic, leading to isolation, anxiety, and depression (Castaneda, 2020).

Recognizing that people have become more hyper-vigilant about their personal hygiene, many restaurants have elevated their safety and cleaning protocols. For example, Country Garden, a property developer in China, recently opened a restaurant complex run entirely by robots. By eliminating human contact, the restaurant complex can ensure high levels of food safety and hygiene, thus alleviating customers' fear of infection or contamination (Davis, 2020). In addition, some valley restaurants in Arizona have deployed ultraviolet disinfection robots to perform sanitization (Stapleton, 2020). Thus, we hypothesize that people that are particularly fearful of contamination are likely to perceive high conditional value of service robots:

H8: *Mysophobia has a positive effect on the conditional value of service robots.*

Attitudes and behavioral intentions

The core assumption underpinning consumer behavior research is that consumers develop positive or negative attitudes toward products or services based on their fondness, which subsequently influences their actual behaviors (González-Rodríguez et al., 2020). In the current study, behavioral intentions are measured in terms of customers' willingness to use and to pay more for robotic restaurants. In the tourism setting, Ivanov and Webster (2019) demonstrated that people who find robot-delivered services appropriate tend to have more favorable attitudes toward and greater inten- tions to use such robots. More recently, Cha (2020) showed that motivated consumer innovativeness can enhance customers' attitudes toward technology, which increases their willingness to interact with robots in restaurants.

Willingness to pay denotes "the maximum amount of money a customer is willing to spend for a product or service" (Homburg et al., 2005, p. 85). This concept can be applied to the price premium, defined by Rao and Bergen (1992) as an additional cost charged above the fair price in exchange for the "true" value of the product (Rao & Bergen, 1992). Rao and Bergen (1992) argued that even small adjustments in product prices can have a profound impact on consumer choice behavior. Therefore, under- standing how much more consumers are willing to pay for bespoke services is crucial for pricing decisions, marketing communication, and new product development (Sarlay & Neuhofer, 2020). As a construct that is directly linked to firm profitability, willingness to pay more has been extensively studied in the tourism and hospitality research. For example, Yadav et al. (2019) found that attitude toward environmental protection is a key determinant of travelers' willingness to pay more for green hotels. More recently, Zhong et al. (2020) examined the impact of robot hotel service (vs. traditional hotel service) on consumers' purchase intentions. Their comparative ana- lyses revealed the that participants who watched a video about a robot-serviced hotel were willing to pay more than those who watched traditional hotel service videos. Thus, we hypothesize:

H9: Customer attitudes have a positive effect on their willingness to use service robots.

H10: Customer attitudes have a positive effect on their willingness to pay more for robotic restaurants.

Based on the ten hypotheses listed above, the conceptual model depicted in Figure 1 was developed.

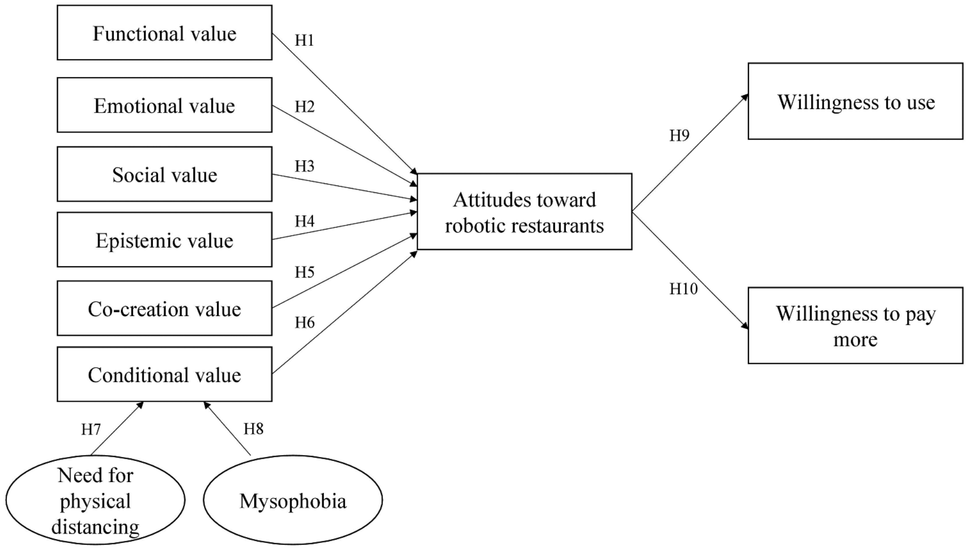

Figure 1. Conceptual model.

Methodology

Data collection

Data required to test the study hypotheses were collected from April 16th to 22nd, 2021. As fully robotized restaurants have not yet been commercialized in Taiwan, it is important to understand the consumption values of potential customers and their willingness to use and to pay more for robot-delivered services before investing in robotic technologies. In order to recruit the participants for this study, we distributed the link to an online questionnaire via Facebook and Line, the most popular chat app in Taiwan. At the beginning of the survey, participants were provided a brief definition of robotic restaurants (see Appendix A) to increase their response accuracy. Next, they were presented with two screening questions designed to identify individuals who have dined at any kind of restaurant in Taiwan in the preceding six-month period but have yet to use robot-delivered services in the restaurants, as only those persons were eligible for participation in the study.

Following the contemporary practices in related research (e.g., Y. Choi et al., 2020b; Hwang et al., 2020; Lee et al., 2021), we invited the participants to watch a short video (lasting 2 min and 45s), which clearly explained the overall system and operation of robot-delivered services in restaurants (see Appendix A), after which they were instructed to complete a questionnaire specifically designed for this study. Although 480 responses were obtained, only 445 were usable, as the remaining 35 responses failed to fulfill the afore-mentioned respondent criteria and exhibited straight-lining issues. The demographic profile of the respondents is provided in Table 1.

Table 1. Profiles of respondents.

Characteristics		Frequency	Percent
Gender			
	Male	213	47.9
	Female	232	52.1
Age			
	18–24	112	25.2
	25–34	143	32.1
	35–44	125	28.1
	45–54	54	12.1
	55 or above	11	2.5
Education			
	High school	58	13.0
	Junior college/College	76	17.1
	Bachelor's degree	245	55.1
	Postgraduate degree	66	14.8
Monthly income (NTD)			
	20,000 or below	45	10.1
	20,001–30,000	127	28.5
	30,001–40,000	132	29.7
	40,001–50,000	89	20.0
	Above 50,000	52	11.7

Measures

Whenever possible, we adapted the measures from well-established sources as shown in Table 2. We asked participants to indicate their willingness to pay on a symmetric, numerical rating scale with positive values (1 to 10%, 11 to 20%, and more than 20%) on the right side and negative values (−1 to −10%, −11 to −20%, and more than −20%) on the left side of the scale. Attitude was measured on a 7-point semantic differential scale (with the endpoints of very bad/very good, very unpleasant/very pleasant, and strongly dislike/strongly like), whereas the remaining constructs were assessed using a 7-point Likert scale (anchored at 1 = "strongly disagree" and 7 = "strongly agree"). The survey instrument was first developed in English and then translated into Chinese using standard back-translation. We pretested the translated questionnaire with 30 restaurant patrons to ensure its readability, clarity, and face validity.

Common method bias

Both procedural and statistical remedies were employed to control for the common method bias. In terms of procedural remedies, respondents were guaranteed anonym- ity, and were informed that their honest opinions mattered the most, given that there were no right or wrong answers (Podsakoff et al., 2003). Regarding statistical remedies, Harman's single-factor test was conducted, indicating that the first factor accounted for 37.54% of the total variance, which was well below the 50% threshold. In addition, the full collinearity test showed that the value of pathological variance inflation factor (VIF) was within the 1.175 − 2.681 range, and was thus below the 3 threshold (J. F. Hair et al., 2019). These findings confirm that common method bias does not pose a threat to this study.

Table 2. Survey items and results of the measurement model.

	Loadings	rho (pA)	AVE
Attitudes toward robotic restaurants (adapted from Curran & Meuter, 2005)		0.929	0.876
How good or bad do you feel about interacting with robots in restaurants?	0.924		
How pleasant or unpleasant it is to interact with robots in restaurants?	0.956		
How much would you say that you like or dislike interacting with robots in restaurants?	0.928		
Co-creation value (adapted from Algharabat, 2018)		0.872	0.869
When interacting with robots, I could feel that I have participated in the process of creating my own dining experience.	0.920		
Interacting with robots could give me lots of autonomy in creating the dining experience I wanted.	0.945		
Conditional value (inspired by Bieller, 2020)		0.903	0.837
I value the efforts of robots in making food preparation/delivery more hygienic during the COVID-19 pandemic.	0.894		
I value the efforts of robots in cleaning and sanitizing the restaurants during the COVID-19 pandemic.	0.918		
I value the efforts of robots in reducing the risk of virus transmission during the COVID-19 pandemic.	0.931		
Emotional value (adapted from Lu et al., 2019)		0.855	0.697
Interacting with robots in restaurants is fun.	0.844		
Interacting with robots in restaurants is entertaining.	0.852		
Interacting with robots in restaurants is enjoyable.	0.824		
The actual process of interacting with robots in restaurants would be pleasant.	0.818		
Epistemic value (Ha & Jang, 2012)		0.859	0.775
Dining at robotic restaurants could satisfy my sense of curiosity.	0.881		
Dining at robotic restaurants could give me an opportunity to learn new things.	0.892		
Dining at robotic restaurants would be a new experience that is different from my ordinary life.	0.867		
Functional value (adapted from Lu et al., 2019)		0.888	0.749
Restaurant services provided by robots are more accurate with less human errors.	0.880		
Restaurant services provided by robots are more dependable than human employee services.	0.888		
Robots could deliver more consistent restaurant services than human employees.	0.907		
Robots could deliver more faster restaurant services than human employees.	0.780		
Mysophobia (inspired by Zemke et al., 2015)		0.841	0.755
It worries me that I may be infected with the coronavirus if my food order is taken by human employees.	0.875		
It worries me that I may be infected with the coronavirus if my food is delivered by human employees.	0.885		
I feel uneasy eating food prepared by human chefs during the COVID-19 pandemic.	0.846		
Need for physical distancing (inspired by ECDC, 2020)		0.875	0.794
I must avoid close contact with other people in restaurants.	0.869		
I must distance myself physically from other people in restaurants.	0.882		
I must maintain a safe distance from other people in restaurants.	0.921		
Social value (adapted from Hwang et al., 2019)		0.786	0.700
Dining at robotic restaurants could impress others.	0.820		
Dining at robotic restaurants could show that I am an early adopter.	0.854		
Dining at robotic restaurants could distinguish me from others.	0.836		
Willingness to pay more (adapted from Webster & Ivanov, 2020)		N/A	N/A
If you were to be served entirely by robots in a restaurant, instead of human employees, how much would you be willing to pay for a fully robotized service compared to a service fully delivered by human employees? (more than −20%, −11 to −20%, −1 to −10%, 0, 1 to 10%, 11 to 20%, more than 20%)	N/A		
Willingness to use (adapted from Gursoy et al., 2019)		0.854	0.763
I am willing to receive services delivered by robots in restaurants.	0.870		
I will feel happy to interact with robots in restaurants.	0.912		
I am likely to interact with robots in restaurants.	0.838		

Loadings, rho (pA), and AVE are not available for single item measures.

Data analysis

The proposed conceptual model was tested utilizing partial least squares-structural equation modeling (PLS-SEM) through SmartPLS 3.3.2. A variance-based SEM was deemed most appropriate for the present study, as its objective is to extend the existing structural theory (theory of consumption values) and to assess a set of predictive relationships (customer perceived value, attitude, and behavioral inten- tion). This approach contrasts with covariance-based SEM which should be adopted for testing or confirming theories (J.F. Hair et al., 2017). Following the two-stage analytical procedure, the measurement model was evaluated before the structural model.

Results

Measurement model

To ensure the quality of the measurement model, its reliability and validity were assessed. As shown in Table 2, all constructs exhibited values of Dijkstra-Henseler's rho (pA) greater than 0.7 (J. F. Hair et al., 2019), implying high internal consistency reliability. Furthermore, the indicator loadings and the average variance extracted (AVE), which represent convergent validity, exceeded 0.708 (J.F. Hair et al., 2017) and 0.5 (Fornell & Larcker, 1981), respectively. In addition, as evident from the results reported in Table 3, the heterotrait-monotrait ratio of correlations (HTMT) values for all constructs were below the threshold value of 0.85 (Henseler et al., 2015), indicating that discriminant validity was achieved.

Structural model

Prior to analyzing the structural model, multicollinearity was examined. The results indicated that all VIFs were below the threshold value of 3 (ranging from 1.032 to 2.253), suggesting that multicollinearity was not an issue in this study (J.F. Hair et al., 2017). Next, bootstrapping procedure with 5,000 subsamples was applied to test the significance of the relationships. Table 4 (Figure 2) shows that functional value ($\beta = 0.314$, $p < .001$), emotional

Table 3. Discriminant validity.

	1	2	3	4	5	6	7	8	9	10	11
1. Attitudes toward robotic restaurants											
2. Co-creation value	0.443										
3. Conditional value	0.733	0.346									
4. Emotional value	0.673	0.303	0.617								
5. Epistemic value	0.692	0.246	0.551	0.505							
6. Functional value	0.811	0.405	0.632	0.620	0.689						
7. Mysophobia	0.324	0.214	0.446	0.328	0.273	0.293					
8. Need for physical distancing	0.302	0.114	0.413	0.207	0.230	0.302	0.207				
9. Social value	0.607	0.376	0.471	0.459	0.464	0.629	0.260	0.188			
10. Willingness to pay more	0.492	0.156	0.435	0.478	0.562	0.533	0.227	0.136	0.457		
11. Wilingness to use	0.628	0.226	0.528	0.575	0.629	0.660	0.222	0.186	0.602	0.796	

Shaded boxes are the standard reporting format for HTMT ratios.

value (H2: $\beta = 0.153$, $p < .001$), social value ($\beta = 0.095$, $p < .01$), epistemic value ($\beta = 0.183$, $p = .001$), co-creation value (H5: $\beta = 0.099$, $p < .01$), and conditional value ($\beta = 0.255$, $p < .001$) have a positive effect on customer attitudes toward robotic restaurants. Notably, the need for physical distancing ($\beta = 0.307$, $p < .001$) and mysophobia ($\beta = 0.334$, $p < .001$) signifi- cantly influence conditional value. Furthermore, attitude was found to be positively related to customers' willingness to use ($\beta = 0.559$, $p < .001$) and pay more for robotic restaurants ($\beta = 0.475$, $p < .001$). Therefore, all ten hypotheses were supported.

To assess the predictive accuracy of the model, the coefficient of determination (R^2) was examined. Figure 2 illustrates that R^2 values ranged from 0.225 (willingness to pay more) to 0.695 (attitudes). This finding suggests that a moderate to substantial amount of variance in the endogenous constructs was explained by the corresponding predictor constructs (Cohen, 1988). Furthermore, the effect size (f^2) was examined to determine the relative effect of a predictor construct on an endogenous variable, where values of 0.02, 0.15, and 0.35 represent small, medium, and large effects, respectively (Cohen, 1988). Table 4 shows that all customer value dimensions had small effect sizes – ranging from 0.02 (social value) to 0.143 (functional value) – on attitudes. With regards to conditional value, the effect sizes for need for physical distancing (0.121) and mysophobia (0.143) are small. Moreover, attitude had a medium effect size on willingness to pay more for robotic services (0.291) and a large effect size (0.454) on willingness to use robots. Finally, the predictive relevance of the model was assessed using the blindfolding procedure. Figure 2 indicates that the Q^2 values of all endogenous constructs were positive (ranging from 0.199 to 0.599), suggesting high predictive relevance of the model (J.F. Hair et al., 2017). Based on these findings, the model is deemed fit, with a standardized root mean square residual (SRMR) value of 0.043, which is well below the 0.08 threshold (Hu & Bentler, 1999).

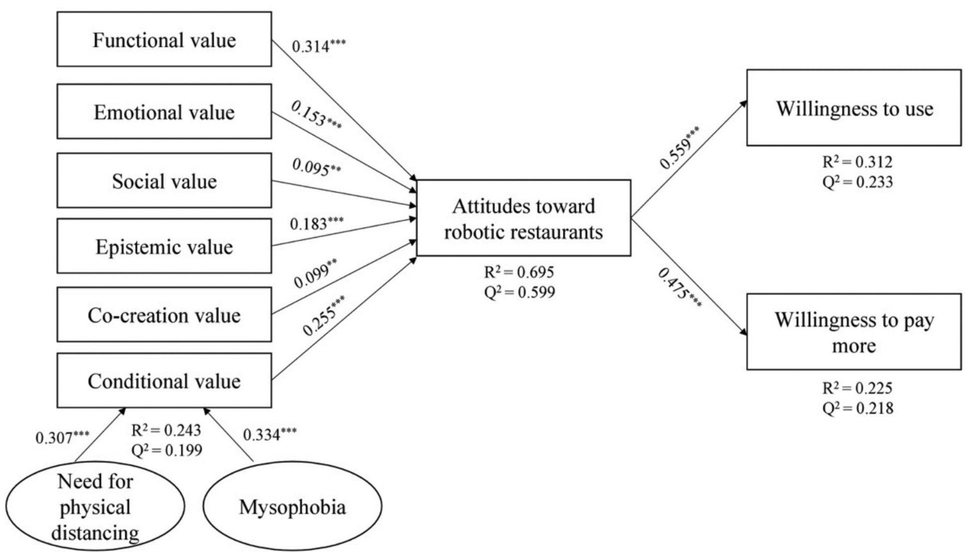

Figure 2. Results of the structural model. Notes: **$p < .01$; ***$p < .001$

Table 4. Results of hypotheses testing.

Hypothesis	Path	β	*t*-value	*p*-value	f^2	Decision
H1	Functional value →Attitudes	0.314	6.475	0.000	0.143	Supported
H2	Emotional value →Attitudes	0.153	3.897	0.000	0.047	Supported
H3	Social value →Attitudes	0.095	2.840	0.005	0.020	Supported
H4	Epistemic value →Attitudes	0.183	4.449	0.000	0.066	Supported
H5	Co-creation value →Attitudes	0.099	3.040	0.002	0.027	Supported
H6	Conditional value →Attitudes	0.255	5.740	0.000	0.121	Supported
H7	Need for physical distancing → Conditional value	0.307	6.856	0.000	0.121	Supported
H8	Mysophobia →Conditional value	0.334	7.488	0.000	0.143	Supported
H9	Attitudes →Willingness to use	0.559	13.831	0.000	0.454	Supported
H10	Attitudes →Willingness to pay more	0.475	11.375	0.000	0.291	Supported

Discussion

The aim of the present study was to explore the relationship between customer perceived value, attitudes, and behavioral intentions toward robotic restaurants in the COVID-19 era. The PLS-SEM analysis showed that customers' attitudes toward robotic restaurants are significantly influenced by their perceptions of robots' functional value, followed by conditional, epistemic, emotional, co-creation, and social values. Notably, the need for physical distancing and mysophobia emerged as two crisis-specific antecedents to conditional value. As a result, attitudes positively influence customers' willingness to use and to pay more for robotic restaurants.

Theoretical implications

The present study contributes to the literature on AI, robotic technologies, crisis management, and hospitality management on several fronts. First, our investigation represents a pioneering attempt to understand customer value perceptions of service robots in restaurants during the COVID-19 pandemic. The COVID-19 pandemic has rapidly transformed consumer behavior in multiple ways, as people are growing more comfortable with AI and robotic technologies, are starting to exhibit strong preferences for contactless ordering and payment options, and are more concerned with health and hygiene issues (Feber et al., 2020). However, majority of extant studies on the use of robots in the tourism and hospitality domain were undertaken before the crisis (e.g., Cha, 2020; De Kervenoael et al., 2020; Zemke et al., 2020). Therefore, their findings cannot elucidate how customers perceive the value of service robots and whether they are willing to use and pay more for robot-delivered services in times of crisis (Seyitoğlu & Ivanov, 2020a). Moreover, authors of early robotic studies examined only a narrow aspect of the perceived value of technology. For example, De Kervenoael et al. (2020) considered perceived value as a unidimensional phenomenon, whereas Cha (2020) presented it as a trade-off between multiple benefits (perceived enjoyment and trust) and sacrifices (perceived risks). While Sheth et al. (1991) offer a broader perspective regarding consumption value, the framework they adopted focuses primarily on functional, emotional, social, epistemic, and conditional attributes, without encapsulating the collaborative capabilities of service robots (Severinson-Eklundh et al., 2003). Sánchez-Fernández and Iniesta-Bonillo (2007) supported this strategy by asserting that perceived value is context- and situation-dependent. Thus, by incorporating co-creation value and crisis-related antecedents into the theory of consumption values, our study provides a more holistic understanding of customers' value perceptions of service robots in a restaurant setting.

The results yielded by our investigation revealed that functional value is the most salient determinant of customer attitudes toward robotic restaurants. This finding is in line with the results reported by De Kervenoael et al. (2020), highlighting the importance of perceived usefulness in shaping visitors' value evaluation and their intention to use social robots. However, it is not fully supported by the observations made by other researchers before the pandemic. For instance, Cha (2020) showed that customers' attitudes toward robot-serviced restaurants are determined by hedonically and socially motivated consumer innovativeness, but not by functionally motivated consumer innovativeness. Likewise, Lin et al. (2020) demonstrated that, compared to performance expectancy, hedonic motivation has a greater influence on hotel guests' emotions toward the use of AI and robotic devices. A possible explanation for this incongruence is that the COVID-19 pandemic has unveiled the previously overlooked functional facets of service robots in managing this global crisis and has reshaped consumers' views of robots beyond their overly emphasized entertainment function. In our analyses, conditional value emerged as the second most important determinant of customer attitudes. Although conditional value has largely been neglected in prior studies, our findings showed that the COVID-19 pandemic has highlighted the importance of robots in mitigating the risk of virus transmission, especially in high-contact services. Our investigation is also among the first to confirm that the need for physical distancing and mysophobia are the antecedents to conditional value, thus heeding Gursoy and Chi (2020) urgent call for more empirical research on consumers' psychological and behavioral responses to the COVID-19 crisis. Our findings also support the argument made by Wen et al. (2020) that the COVID-19 pandemic is changing consumer behavior as people are more concerned than ever about restaurant hygiene and safety standards.

Epistemic value as the third most important determinant of customer attitudes toward robotic restaurants. Authors of previous studies in this domain have investigated hotel guest experiences with service robots and have found that interactions with robots constitute a novel experience (Y. Choi et al., 2020b; Tung & Au, 2018). However, consumer perceptions of service robots in the restaurant setting remain insufficiently studied. To the best of our knowledge, this is the first attempt to empirically examine how the perceived epistemic value or novelty of service robots enhances customer attitudes and behaviors. We also found that hedonic value remains salient in creating favorable customer attitudes toward robotic restaurants. This finding is supported by previous studies illustrating that hedonic motivation can elicit positive emotions toward using AI devices in general (Gursoy et al., 2019), and particularly in the hospitality context (Lin et al., 2020).

In our analyses, co-creation value has emerged as a relatively important determinant of customer attitudes toward robotic restaurants. This finding substantiates the core SDL pre- mise that value is not only created for but also collaboratively created with customers through the mediation of smart technologies such as AI-driven robots (Prahalad & Ramaswamy, 2004; Vargo & Lusch, 2004). According to Čaić et al. (2019), social functionalities are incorporated into service robots, allowing them to communicate, interact, and collaborate with users. While prior research in this field has exclusively focused on the interactive capabilities of service robots (e.g., Y. Choi et al., 2020b; Wirtz et al., 2018), our study goes further to suggest that the value co-created during this interaction process can engender favorable customer attitudes. By addressing the collaborative aspect of service robots, this investigation enriches the theory of consumption values through the integration of SDL perspective. Consistent with the results reported by Hwang et al. (2019), we revealed that social value is the least important determinant of customer attitudes. One possible explanation for this result is that the COVID-19 pandemic has brought the health and safety concerns to the forefront of consumers' minds. Hence, they would primarily use robots in restaurants to protect themselves from infection, while placing less value on creating an impression of being tech-savvy.

Finally, given that most of the extant robotic studies focus on a single outcome variable such as acceptance and intention to use (e.g., Cha, 2020; De Kervenoael et al., 2020; Wirtz et al., 2018), several scholars (e.g., Kuo et al., 2017; Seyitoğlu & Ivanov, 2020a) have called for more empirical studies on the financial target constructs such as willingness to pay more. Responding to this call, we elucidated the effect of customers' attitudes on their willingness to pay more for

robotic restaurants. Based on the findings of this investigation, investment into service robots is justifiable in the Taiwanese restaurant business, as it would be a viable financial decision with a high potential for return on investment.

Practical implications

Restaurants around the world are struggling to maintain momentum due to labor shortages, fewer dine-in customers, and revenue losses caused by the coronavirus pandemic. While this unprecedented global catastrophe has accelerated the incorporation of contactless technologies into restaurant operations, blindly investing in robotic technologies without understanding customers' willingness to use and to pay more for robot-delivered services may lead to wasted resources or even bankruptcy. The findings yielded by this empirical study offer significant implications for restaurateurs considering incorporating AI and robotic technologies into their operations.

The findings of this research indicate that functional and conditional values are the two most important factors influencing customers' attitudes toward robotic restaurants. Notably, the importance of conditional value is amplified by the need for physical distan- cing and mysophobia. In order to emphasize the functional value of robot-driven service, restaurateurs should use promotional videos to showcase the robots' ability to deliver faster, more reliable, and more consistent services than human employees. For example, when Country Garden launched a robotics restaurant complex in Foshan, it emphasized the fact that droid waiters can serve almost 600 customers at once as hundreds of robot-cooked meals can be prepared in 20 seconds (Jiang, 2020). Restaurant managers should also work with technology companies to improve the competency of service robots in performing more complex tasks such as answering difficult questions and handling customer com- plaints which are currently reserved for human employees. In a (post-)pandemic world, restaurateurs should pay special attention to the conditional value of service robots. For example, they can highlight the use of service robots to make food preparation more hygienic and for contactless, socially distanced ordering.

Our findings also show that epistemic value is the third most important factor in creating favorable attitudes toward robotic restaurants. Thus, in order to satisfy customers' desire for novel dining experience, restaurateurs need to work with robot manufacturers and interior designers to truly deliver something unique and groundbreaking. However, to adapt and thrive in the "new normal," restaurant design should be a balance between innovation and social distancing. For example, protective barriers such as lampshade-like plastic shields and individual robot-themed cabins can be used to segregate dinners in an attempt to minimize the risk of contagion and restore customer confidence. In addition, restaurateurs may need to reconfigure how diners queue and wait for their orders, or may limit the time they can spend consuming their food on premises.

Emotional value and co-creation were found to significantly influence customers' attitudes toward robotic restaurants. Therefore, given that enforcing social distancing may cause psychological issues such as loneliness (Seyitoğlu & Ivanov, 2020b), restaurateurs can use service robots to entertain and engage the diners. For example, Pepper Parlor Café in Tokyo deploys humanoid robots to take selfies with diners and amuse them by dancing and playing games. Another unique selling proposition that robotic restaurants can consider is a memorable dining experience co-created by robots and diners. Instead of offering standard menu items, restaurateurs should allow customers to co-create their own meals with service robots. While customers can freely choose the ingredients, cooking methods, portion size, and food presentation, service robots can be trained to review their recipes and give them suggestions. To attract socially motivated customers, restaurant managers must incorporate some cool and trendy elements into the interior design so that diners can impress others by sharing their experience on social media. Apart from futuristic dining environments, offering "photo worthy" meals and fun interaction moments with robots may spark potential social media postings. As the pandemic has fundamentally changed what consumers value, as well as how and where they eat, our findings provide useful guidance for restaurateurs on how to adjust their operations according to the emerging consumer needs in a new reality.

Limitations and future research

This study has several limitations which should be considered when interpreting the findings reported in the preceding sections. First, since robotic restaurants are yet to be widely accessible in Taiwan, only the views of potential diners could be considered in the analyses. Thus, to enhance the generalizability of our findings, authors of future studies in this field should replicate the model proposed in this work using information provided by actual diners from different geographical locations. Additional investigations into the moderating role of experience are also warranted, given that those consumers who have dined at robotic restaurants may develop different attitudes and behavioral intentions compared to those without any prior dining experience. Second, this study focused on customer value perceptions and attitudes in relation to their willingness to use and to pay more for robotic restaurants. Hence, in future research, the demographic (gender, age, income) and personal (innovativeness, extraversion, openness to new experiences) characteristics of customers who are highly willing to pay more for robotic restaurants should also be assessed. Third, as in our survey we did not specify a restaurant type, it would be interesting to investigate whether customers' willingness to pay varies across different restaurant types, such as limited-service and full-service restau- rants. Finally, as the main purpose of this study was to highlight the impact of the COVID-19 pandemic on consumer behavior, we focused solely on the crisis-related variables as the antecedents to conditional value. This restriction should be addressed in future research by incorporating the antecedents of other value dimensions, such as anthropomorphism, warmth, competence, and social intelligence.

Funding

This study was partly supported by a research fund from Ministry of Science and Technology, Taiwan.

References

Adapa, S., Fazal-e-hasan, S. M., Makam, S. B., Azeem, M. M., & Mortimer, G. (2020). Examining the antecedents and consequences of perceived shopping value through smart retail technology. *Journal of Retailing and Consumer Services*, *52*, 101901. https://doi.org/10.1016/j.jretconser.2019.101901

Algharabat, R. S. (2018). The role of telepresence and user engagement in co-creation value and purchase intention: Online retail context. *Journal of Internet Commerce*, *17*(1), 1–25. https://doi.org/10.1080/15332861.2017.1422667

Babin, B. J., Darden, W. R., & Griffin, M. (1994). Work and/or fun: Measuring hedonic and utilitarian shopping value. *Journal of Consumer Research*, *20*(4), 644–656. https://doi.org/10.1086/209376

Belanche, D., Casaló, L. V., Flavián, C., & Schepers, J. (2020). Service robot implementation: A theoretical framework and research agenda. *The Service Industries Journal*, *40*(3–4), 203–225. https://doi.org/10.1080/02642069.2019.1672666

Bieller, S. (2020). *Robots on the front line of keeping people safe from the coronavirus*. International Federal of Robotics. https://ifr.org/post/robots-on-the-front-line-of-keeping-people-safe-from-the-coronavirus

Bogue, R. (2020). Robots in a contagious world. *Industrial Robot: The International Journal of Robotics Research and Application*, *47*(5), 642–673. https://doi.org/10.1108/IR-05-2020-0101

Čaić, M., Mahr, D., & Oderkerken-Schröder, G. (2019). Value of social robots in services: Social cognition perspective. *Journal of Services Marketing*, *33*(4), 463–478. https://doi.org/10.1108/JSM-02-2018-0080

Campos, A. C., Mendes, J., Valle, P. O. D., & Scott, N. (2018). Co-creation of tourist experiences: A literature review. *Current Issues in Tourism*, *21*(4), 369–400. https://doi.org/10.1080/13683500.2015.1081158

Castaneda, R. (2020). *Coping with Germaphobia during the Coronavirus crisis*. U.S. News & World Report. https://health.usnews.com/health-care/conditions/articles/coping-with-coronavirus-as-a-germaphobe

Cha, S. S. (2020). Customers' intention to use robot-serviced restaurants in Korea: Relationship of coolness and MCI factors. *International Journal of Contemporary Hospitality Management*, *32*(9), 2947–2968. https://doi.org/10.1108/IJCHM-01-2020-0046

Chan, A. P. H., & Tung, V. W. S. (2019). Examining the effects of robotic service on brand experience: The moderating role of hotel segment. *Journal of Travel & Tourism Marketing*, *36*(4), 458–468. https://doi.org/10.1080/10548408.2019.1568953

Chan, K. W., Yim, C. K., & Lam, S. S. (2010). Is customer participation in value creation a double-edged sword? Evidence from professional financial services across cultures. *Journal of Marketing*, *74*(3), 48–64. https://doi.org/10.1509/jmkg.74.3.048

Choi, J., Madhavaram, S. R., & Park, H. Y. (2020a). The role of hedonic and utilitarian motives on the effectiveness of partitioned pricing. *Journal of Retailing*, *96*(2), 251–265. https://doi.org/10.1016/j.jretai.2019.10.003

Choi, Y., Choi, M., Oh, M., & Kim, S. (2020b). Service robots in hotels: Understanding the service quality perceptions of human-robot interaction. *Journal of Hospitality Marketing & Management*, *29*(6), 613–635. https://doi.org/10.1080/19368623.2020.1703871

Christopher, M. (1996). From brand values to customer value. *Journal of Marketing*, *2*(1), 55–66. https://doi.org/10.1108/EUM0000000000007

Chuah, S. H. W., & Yu, J. (2021). The future of service: The power of emotion in human-robot interaction. *Journal of Retailing and Consumer Services*, *61*, 102551. https://doi.org/10.1016/j.jretconser.2021.102551

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed.). Lawrence Erlbaum Associates.

Curran, J. M., & Meuter, M. L. (2005). Self-service technology adoption: Comparing three technologies. *Journal of Services Marketing*, *19*(2), 103–113. https://doi.org/10.1108/08876040510591411

Dabholkar, P. A., & Bagozzi, R. P. (2002). An attitudinal model of technology-based self-service: Moderating effects of consumer traits and situational factors. *Journal of the Academy of Marketing Science*, *30*(3), 184–201. https://doi.org/10.1177/0092070302303001

Datassential (2020a). *One table: Consumer insights and the path forward*. Datassential. https://datassential.com/wp-content/uploads/2020/06/Datassential-ONE-TABLE-Consumer-Report-F.pdf

Datassential (2020b). *Covid-19 report: Here I come*. Datassential. https://datassential.com/wp-content/uploads/2020/05/Datassential-Coronavirus19-05-20-20.pdf

Davis, K. (2020). *Welcome to China's latest 'robot restaurant'*. World Economic Forum. https://www.weforum.org/agenda/2020/07/china-robots-ai-restaurant-hospitality/

De Kervenoael, R., Hasan, R., Schwob, A., & Goh, E. (2020). Leveraging human-robot interaction in hospitality services: Incorporating the role of perceived value, empathy, and information sharing into visitors' intentions to use social robots. *Tourism Management*, *78*, 104042. https://doi.org/10.1016/j.tourman.2019.104042

Dube, K., Nhamo, G., & Chikodzi, D. 2020. COVID-19 cripples global restaurant and hospitality industry. *Current Issues in Tourism*, *24*(11), 1487-1490. https://doi.org/10.1080/13683500.2020.1773416

Eastman, J. K., Goldsmith, R. E., & Flynn, L. R. (1999). Status consumption in consumer behavior: Scale development and validation. *Journal of Marketing Theory and Practice*, *7*(3), 41–52. https://doi.org/10.1080/10696679.1999.11501839

ECDC (2020). *Considerations relating to social distancing measures in response to COVID-19 – Second update*. ECDC. https://www.ecdc.europa.eu/en/publications-data/considerations-relating-social-distancing-measures-response-covid-19-second

ET Retail (2020). *Restaurants open but grapple with decreased sales, few dine-in customers*. ET Retail. https://retail.economictimes.indiatimes.com/news/food-entertainment/food-services/restaurants-open-but-grapple-with-decreased-sales-few-dine-in-customers/76931693

Fabius, V., Kohli, S., & Timelin, B. (2020). *Meet the next-normal consumer*. Mckinsey & Company. https://www.mckinsey.com/business-functions/marketing-and-sales/our-insights/meet-the-next-normal-consumer

Feber, D., Granskog, A., Lingqvist, O., & Nordigården, D. (2020). *Sustainability in packaging: Inside the mind of US consumers*. Mckinsey & Company. https://www.mckinsey.com/industries/paper-forest-products-and-packaging/our-insights/sustainability-in-packaging-inside-the-minds-of-us-consumers

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, *18*(1), 39–50. https://doi.org/10.2307/3151312

Goffman, E. (1959). *The presentation of self in everyday life*. Double Day.

González-Rodríguez, M. R., Díaz-Fernández, M. C., & Font, X. (2020). Factors influencing willingness of customers of environmentally friendly hotels to pay a price premium. *International Journal of Contemporary Hospitality Management*, *32*(1), 60–80. https://doi.org/10.1108/IJCHM-02-2019-0147

Grubb, E. L., & Grathwohl, H. L. (1967). Consumer self-concept, symbolism and market behavior: A theoretical approach. *Journal of Marketing*, *31*(4), 22–27. https://doi.org/10.2307/1249461

Guarente, G. (2020). *Fremont brewing reopens less than a week after its COVID-19-related closure*. Eater Seattle. https://seattle.eater.com/2020/6/17/21293975/fremont-brewing-closes-employee-tests-positive-for-covid-19

Gursoy, D., & Chi, C. G. (2020). Effects of COVID-19 pandemic on hospitality industry: Review of the current situations and a research agenda. *Journal of Hospitality Marketing & Management*, *29*(5), 527–529. https://doi.org/10.1080/19368623.2020.1788231

Gursoy, D., Chi, O. H., Lu, L., & Nunkoo, R. (2019). Consumers acceptance of artificially intelligent (AI) device use in service delivery. *International Journal of Information Management*, *49*, 157–169. https://doi.org/10.1016/j.ijinfomgt.2019.03.008

Ha, J., & Jang, S. (2012). Consumer dining value: Does it vary across different restaurant segments? *Journal of Foodservice Business Research*, *15*(2), 123–142. https://doi.org/10.1080/15378020.2012.677378

Haddon, H., & Maidenberg, M. (2020). *Covid-19 risk for workers at restaurants: Cramped kitchens*. The Wall Street Journal. https://www.wsj.com/articles/covid-19-risk-for-workers-at-restaurants-cramped-kitchens-11608892200?mod=e2fb&fbclid=IwAR0sGfpE6E749NH1G2T19oA2YIRRDt-vedg3uuJZr3EDA4gNoYsLqmQtgoQ

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2017). *A primer on partial least squares structural equation modeling (PLS-SEM)* (2nd ed.). Sage Publications.

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review*, *31*(1), 2–24. https://doi.org/10.1108/EBR-11-2018-0203

Hassan, S. B., & Soliman, M. (2020). COVID-19 and repeat visitation: Assessing the role of destination social responsibility, destination reputation, holidaymakers' trust and fear arousal. *Journal of Destination Marketing & Management*, *19*, 100495. https://doi.org/10.1016/j.jdmm.2020.100495

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, *43*(1), 115–135. https://doi.org/10.1007/s11747-014-0403-8

Holbrook, M. B. (1994). The nature of customer's value: An axiology of service in consumption experience. In R. T. Rust & R. L. Oliver (Eds.), *Service quality: New directions in theory and practice* (pp. 21–71). Sage Publications.

Homburg, C., Koschate, N., & Hoyer, W. D. (2005). Do satisfied customers really pay more? A study of the relationship between customer satisfaction and willingness to pay. *Journal of Marketing*, *69*(2), 84–96. https://doi.org/10.1509/jmkg.69.2.84.60760

Hu, L. T., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling: A Multidisciplinary Journal*, *6*(1), 1–55. https://doi.org/10.1080/10705519909540118

Hwang, J., Kim, H., & Kim, W. (2019). Investigating motivated consumer innovativeness in the context of drone food delivery services. *Journal of Hospitality and Tourism Management*, *38*, 102–110. https://doi.org/10.1016/j.jhtm.2019.01.004

Hwang, J., Park, S., & Kim, I. (2020). Understanding motivated consumer innovativeness in the context of a robotic restaurant: The moderating role of product knowledge. *Journal of Hospitality and Tourism Management*, *44*, 272–282. https://doi.org/10.1016/j.jhtm.2020.06.003

Interactions LLC (2020). *The Coronavirus is changing consumer comfort with AI*. Interactions LLC. https://www.interactions.com/press-releases/the-coronavirus-is-changing-consumer-comfort-with-ai/

Ivanov, S., & Webster, C. (2019). Perceived appropriateness and intention to use service robots in tourism. In J. Pesonen & J. Neidhardt (Eds.), *Information and Communication Technologies in Tourism* (pp. 237–248). Springer.

Ivanov, S., Seyitoğlu, F., & Markova, M. (2020). Hotel managers' perceptions towards the use of robots: A mixed-methods approach. *Information Technology & Tourism*, *22*(4), 505–535. https://doi.org/10.1007/s40558-020-00187-x

Jiang, E. (2020). *China opens a restaurant manned entirely by robots, including droid waitresses, automated baristas and AI-powered chefs*. MailOnline. https://www.dailymail.co.uk/news/article-8478771/China-opens-futuristic-restaurant-solely-manned-AI-powered-robots.html

Jiang, Y., & Kim, Y. (2015). Developing multi-dimensional green value: Extending Social Exchange Theory to explore customers' purchase intention in green hotels – Evidence from Korea. *International Journal of Contemporary Hospitality Management*, *27*(2), 308–334. https://doi.org/10.1108/IJCHM-08-2013-0383

Joshi, N. (2020). *Bon Appétit! Robotic restaurants are the future*. Forbes. https://www.forbes.com/sites/cognitiveworld/2020/02/03/bon-apptit-robotic-restaurants-are-the-future/?sh= 34fac3dd2136

Jung, T. H., & Tom Dieck, M. C. (2017). Augmented reality, virtual reality and 3D printing for the co-creation of value for the visitor experience at cultural heritage places. *Journal of Place Management and Development*, *10*(2), 140–151. https://doi.org/10.1108/JPMD-07-2016-0045

Kaartemo, V., & Helkkula, A. (2018). A systematic review of artificial intelligence and robots in value co-creation: Current status and future research avenues. *Journal of Creating Value*, *4*(2), 211–228. https://doi.org/10.1177/2394964318805625

Khoa, D. T., Wang, C. Y., & Guchait, P. (2020). Using regulatory focus to encourage physical distancing in services: When fear helps to deal with Mr. Deadly COVID-19. *The Service Industries Journal*, *41*(1–2), 32–57. https://doi.org/10.1080/02642069.2020.1831477

Kim, S. S., Kim, J., Badu-Baiden, F., Giroux, M., & Choi, Y. (2021). Preference for robot service or human service in hotels? Impacts of the COVID-19 pandemic. *International Journal of Hospitality Management*, *93*, 102795. https://doi.org/10.1016/j.ijhm.2020.102795

Kuo, C. M., Chen, L. C., & Tseng, C. Y. (2017). Investigating an innovative service with hospitality robots. *International Journal of Contemporary Hospitality Management*, *29*(5), 1305–1321. https://doi.org/10.1108/IJCHM-08-2015-0414

Laato, S., Islam, A. N., Farooq, A., & Dhir, A. (2020). Unusual purchasing behavior during the early stages of the COVID-19 pandemic: The stimulus-organism-response approach. *Journal of Retailing and Consumer Services*, *57*, 102224. https://doi.org/10.1016/j.jretconser.2020.102224

Lee, Y., Lee, S., & Kim, D. Y. (2021). Exploring hotel guests' perceptions of using robot assistants. *Tourism Management Perspectives*, *37*, 100781. https://doi.org/10.1016/j.tmp.2020.100781

Lever, R., & Jammot, J. (2021). *Pandemic's robot 'heroes' highlight their value at tech show*. INQUIRER.net. https://techxplore.com/news/2021-01-pandemic-robot-heroes-highlight-tech.html#:~:text=Robots%20that%20helped%20people%20survive,momentum%20to%20the%20robotics%20sector

Lin, H., Chi, O. H., & Gursoy, D. (2020). Antecedents of customers' acceptance of artificially intelligent robotic device use in hospitality services. *Journal of Hospitality Marketing & Management*, *29*(5), 530–549. https://doi.org/10.1080/19368623.2020.1685053

Liubchenkova, N. (2020). *In pictures: Restaurants find creative ways to enforce social distancing*. Euronews. https://www.euronews.com/2020/07/20/in-pictures-restaurants-find-creative-ways-to-enforce-social-distancing

Lu, L., Cai, R., & Gursoy, D. (2019). Developing and validating a service robot integration willingness scale. *International Journal of Hospitality Management*, *80*, 36–51. https://doi.org/10.1016/j.ijhm.2019.01.005

Lu, L., Zhang, P., & Zhang, T. C. (2021). Leveraging "human-likeness" of robotic service at restaurants. *International Journal of Hospitality Management*, *94*, 102823. https://doi.org/10.1016/j.ijhm.2020.102823

Marinova, D., De Ruyter, K., Huang, M. H., Meuter, M. L., & Challagalla, G. (2017). Getting smart: Learning from technology-empowered frontline interactions. *Journal of Service Research*, *20*(1), 29–42. https://doi.org/10.1177/1094670516679273

Mathath, A., & Fernando, Y. (2015). Robotic transformation and its business applications in food industry. In Z. Luo (Ed.), *Robotics, automation, and control in industrial and service settings* (pp. 281–305). IGI Global.

Mathis, E. F., Kim, H. L., Uysal, M., Sirgy, J. M., & Prebensen, N. K. (2016). The effect of co-creation experience on outcome variable. *Annals of Tourism Research*, *57*, 62–75. https://doi.org/10.1016/j.annals.2015.11.023

Murphy, J., Gretzel, U., & Pesonen, J. (2019). Marketing robot services in hospitality and tourism: The role of anthropomorphism. *Journal of Travel & Tourism Marketing*, *36*(7), 784–795. https://doi.org/10.1080/10548408.2019.1571983

National Institute of Mental Health (2019). *Obsessive-compulsive disorder*. https://www.nimh.nih.gov/health/topics/obsessive-compulsive-disorder-ocd/index.shtml

National Restaurant Association (2020). *100,000 restaurants closed six months into pandemic*. https://restaurant.org/news/pressroom/press-releases/100000-restaurants-closed-six-months-into-pandemic

National Restaurant Association (2021). *State of the restaurant industry*. National Institute of Mental Health. https://restaurant.org/

Pendrill, K. (2020). *Contactless dining: Everything you need to know*. Touchbistro. https://www.touchbistro.com/blog/guide-to-contactless-dining/

Pihlström, M., & Brush, G. J. (2008). Comparing the perceived value of information and entertainment mobile services. *Psychology & Marketing*, *25*(8), 732–755. https://doi.org/10.1002/mar.20236

Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology*, *88*(5), 879–903. https://doi.org/10.1037/0021-9010.88.5.879

Prahalad, C. K., & Ramaswamy, V. (2004). Co-creation experiences: The next practice in value creation. *Journal of Interactive Marketing*, *18*(3), 5–14. https://doi.org/10.1002/dir.20015

Pura, M. (2005). Linking perceived value and loyalty in location-based mobile services. *Managing Service Quality: An International Journal*, *15*(6), 509–538. https://doi.org/10.1108/09604520510634005

Puttaiah, M., Raverkar, A. K., & Avramakis, E. (2020). *All change: How COVID-19 is transforming consumer behaviour*. Swiss Re Institute. https://www.swissre.com/institute/research/topics-and-risk-dialogues/health-and-longevity/covid-19-and-consumer-behaviour.html

Rao, A. R., & Bergen, M. E. (1992). Price premium variations as a consequence of buyers' lack of information. *Journal of Consumer Research*, *19*(3), 412–423. https://doi.org/10.1086/209311

Ren, S. (2020). *Who could possibly want hot pot right now? Investors*. Bloomberg. https://www.bloomberg.com/opinion/articles/2020-09-02/haidilao-stock-rises-as-diners-consider-smart-restaurants-post-covid

Rigie, A. (2018). *The rise of the restaurant robot*. Forbes. https://www.forbes.com/sites/andrewrigie/2018/09/24/the-rise-of-the-restaurant-robot/?sh=4a004f933747

Robotics Research (2019). *A cafe staffed by robots.*Robotics Research. Retrieve from https://www.roboticsresear.ch/articles/19135/a-cafe-staffed-by-robots

Roggeveen, A. L., & Sethuraman, R. (2020). How the COVID-19 pandemic may change the world of Retailing. *Journal of Retailing*, *96*(2), 169–171. https://doi.org/10.1016/j.jretai.2020.04.002

Sánchez-Fernández, R., & Iniesta-Bonillo, M. Á. (2007). The concept of perceived value: A systematic review of the research. *Marketing Theory*, *7*(4), 427–451. https://doi.org/10.1177/1470593107083165

Sarlay, S., & Neuhofer, B. (2020). Sharing economy disrupting aviation: Travelers' willingness to pay. *Tourism Review*, *ahead-of-print*(ahead–of–print). https://doi.org/10.1108/TR-09-2019-0375 .

Scott, E. (2020). *How to deal with mysophobia – An intense fear of dirt and germs – Amid the coronavirus pandemic*. Metro. https://metro.co.uk/2020/06/18/how-deal-mysophobia-immense-fear-germs-amid-coronavirus-pandemic-12868722/

Severinson-Eklundh, K., Green, A., & Hüttenrauch, H. (2003). Social and collaborative aspects of interaction with a service robot. *Robotics and Autonomous Systems*, *42*(3–4), 223–234. https://doi.org/10.1016/S0921-8890(02)00377-9

Seyitoğlu, F., & Ivanov, S. (2020a). A conceptual framework of the service delivery system design for hospitality firms in the (post-) viral world: The role of service robots. *International Journal of Hospitality Management*, *91*, 102661. https://doi.org/10.1016/j.ijhm.2020.102661

Seyitoğlu, F., & Ivanov, S. 2020b. Service robots as a tool for physical distancing in tourism. *Current Issues in Tourism*, *Futures* (ahead–of–print). https://doi.org/10.1080/13683500.2020.1774518 .

Seyitoğlu, F., & Ivanov, S. (2020c). Understanding the robotic restaurant experience: A multiple case study. *Journal of Tourism*, *Futures (ahead–of–print)*.. https://doi.org/10.1108/JTF-04-2020-0070

Sheth, J. (2020). Impact of Covid-19 on consumer behavior: Will the old habits return or die? *Journal of Business Research*, *117*, 280–283. https://doi.org/10.1016/j.jbusres.2020.05.059

Sheth, J. N., Newman, B. I., & Gross, B. L. (1991). Why we buy what we buy: A theory of consumption values. *Journal of Business Research*, *22*(2), 159–170. https://doi.org/10.1016/0148-2963(91)90050-8

Shin, H. (2020). *South Korean cafe hires robot barista to help with social distancing*. Thomson Reuters. https://www.reuters.com/article/us-health-coronavirus-southkorea-robots-idUSKBN2310T9

Shukla, P. (2012). The influence of value perceptions on luxury purchase intentions in developed and emerging markets. *International Marketing Review*, *29*(6), 574–596. https://doi.org/10.1108/02651331211277955

Sigala, M. (2020). Tourism and COVID-19: Impacts and implications for advancing and resetting industry and research. *Journal of Business Research*, *117*, 312–321. https://doi.org/10.1016/j.jbusres.2020.06.015

Stapleton, E. (2020). *Valley restaurant owners using UV light technology to disinfect before*. UV Purify. https://uvpurify.org/blogs/news/valley-restaurant-owners-using-uv-light-technology-to-disinfect-before-reopening#:~:text=View%20more-,Valley%20restaurant%20owners%20using%20UV%20light%20technology%20to%20disinfect%20before,with%20help%20from%20a%20robot .

Sweeney, J. C., & Soutar, G. N. (2001). Consumer perceived value: The development of a multiple item scale. *Journal of Retailing*, *77*(2), 203–220. https://doi.org/10.1016/S0022-4359(01)00041-0

Teng, C. C., & Chang, J. H. (2013). Mechanism of customer value in restaurant consumption: Employee hospitality and entertainment cues as boundary conditions. *International Journal of Hospitality Management*, *32*, 169–178. https://doi.org/10.1016/j.ijhm.2012.05.008

Thomas, Z. (2020). *Coronavirus: Will Covid-19 speed up the use of robots to replace human workers?* BBC News. https://www.bbc.com/news/technology-52340651

Tilley, J. (2017). *Automation, robotics, and the factory of the future*. Mckinsey & Company. https://www.mckinsey.com/business-functions/operations/our-insights/automation-robotics-and-the-factory-of-the-future

Tung, V. W. S., & Au, N. (2018). Exploring customer experiences with robotics in hospitality. *International Journal of Contemporary Hospitality Management*, *30*(7), 2680–2697. https://doi.org/10.1108/IJCHM-06-2017-0322

Vargo, S. L., & Lusch, R. F. (2004). Evolving to a new dominant logic for marketing. *Journal of Marketing*, *68*(1), 1–17. https://doi.org/10.1509/jmkg.68.1.1.24036

Webster, C., & Ivanov, S. (2020). *Robots in travel, tourism and hospitality: Key findings from a global study*. Zangador.

Wen, J., Kozak, M., Yang, S., & Liu, F. (2020). COVID-19: Potential effects on Chinese citizens' lifestyle and travel. *Tourism Review*, *76*(1), 74–87. https://doi.org/10.1108/TR-03-2020-0110

Williams, P., & Soutar, G. N. (2009). Value, satisfaction and behavioral intentions in an adventure tourism context. *Annals of Tourism Research*, *36*(3), 413–438. https://doi.org/10.1016/j.annals.2009.02.002

Wirtz, J., Patterson, P. G., Kunz, W. H., Gruber, T., Lu, V. N., Paluch, S., & Martins, A. (2018). Brave new world: Service robots in the frontline. *Journal of Service Management*, *29*(5), 907–931. https://doi.org/10.1108/JOSM-04-2018-0119

Wolfe, A. (2018). *Fast casual restaurant with robotic kitchen opens*. EnsembleIQ. https://hospitalitytech.com/fast-casual-restaurant-robotic-kitchen-opens

Woodruff, R. B. (1997). Customer value: The next source for competitive advantage. *Journal of the Academy of Marketing Science*, *25*(2), 139–153. https://doi.org/10.1007/BF02894350

Xinhua (2020). *COVID-19 boosting taste for robot waiters, chefs*. SHINE. https://www.shine.cn/news/nation/2007212570/

Yadav, R., Balaji, M. S., & Jebarajakirthy, C. (2019). How psychological and contextual factors contribute to travelers' propensity to choose green hotels? *International Journal of Hospitality Management*, *77*, 385–395. https://doi.org/10.1016/j.ijhm.2018.08.002

Zeithaml, V. A. (1988). Consumer perceptions of price, quality, and value: A means-end model and synthesis of evidence. *Journal of Marketing*, *52*(3), 2–22. https://doi.org/10.1177/002224298805200302

Zemke, D. M. V., Neal, J., Shoemaker, S., & Kirsch, K. (2015). Hotel cleanliness: Will guests pay for enhanced disinfection? *International Journal of Contemporary Hospitality Management*, *27*(4), 90–710. https://doi.org/10.1108/IJCHM-01–2014-0020

Zemke, D. M. V., Tang, J., Raab, C., & Kim, J. (2020). How to build a better robot . . . For quick-service restaurants. *Journal of Hospitality & Tourism Research*, *44* (8), 1235–1269. in press. https://doi.org/10.1177/1096348020946383

Zeng, Z., Chen, P. J., & Lew, A. A. (2020). From high-touch to high-tech: COVID-19 drives robotics adoption. *Tourism Geographies*, *22*(3), 724–734. https://doi.org/10.1080/14616688.2020.1762118

Zhang, T., Zhang, P., & Lu, L. (2020). Service encounter value and online engagement behaviors. *International Journal of Hospitality Management*, *85*, 102338. https://doi.org/10.1016/j.ijhm.2019.102338

Zhong, L., Sun, S., Law, R., & Zhang, X. (2020). Impact of robot hotel service on consumers' purchase intention: A control experiment. *Asia Pacific Journal of Tourism Research*, *25*(7), 780–798. https://doi.org/10.1080/10941665.2020.1726421

Appendix A. Survey description of robotic restaurants

A robotic restaurant or automated restaurant is one that uses robots to perform tasks such as taking orders, preparing and serving food to customers. Robots are also being used to help maintain social distancing and entertain customers.

Screenshot from the robotic restaurant video
Source: New China TV (https://www.youtube.com/watch?v=YPoAjRxyBQQ)