Building restaurant customers' technology readiness through robot-assisted experiences at multiple product levels

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First Author: Emily Ma, Ph.D.

Title: Professor

Affiliation: School of Hospitality and Tourism Management, University of Surrey, Guildford, UK

Email: emilyma2020@yahoo.com

Second Author: Huijun Yang, Ph.D.

Title: Assistant Professor

Affiliation: School of Hospitality Management, Macao Institute for Tourism Studies, Macao, China

Email: june@ift.edu.mo

Third and Corresponding Author: Yao-Chin Wang, Ph.D.

Title: Assistant Professor

Affiliation: Department of Tourism, Hospitality and Event Management, University of Florida, Gainesville, FL, USA

Address: 1864 Stadium Rd., FLG 186B, P.O. Box 118208, Gainesville, FL 32611, USA

Tel.: +1 352-294-1656

E-mail: wang.yaochin@ufl.edu

Fourth Author: Hanqun Song, Ph.D.

Title: Associate Professor

Affiliation: School of Management, University of Bradford, Bradford, UK

Email: h.song7@bradford.ac.uk

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Abstract

The growing popularity of robot-related research contexts in hospitality and tourism calls for in-depth analysis of how different product/service designs strategies integrating robots may influence customers' experiences. Employing a scenario-based 2×2×2 experimental research design, this study assesses service robots applied at three different product/service levels (i.e., core, facilitating, and augmented). From surveying 378 customers of mid-priced casual restaurants and 312 tourists of a mid-priced theme park restaurant, findings of the study suggest that using robots at all three product/service levels lead to a more positive educational experience but not entertainment experience. The study further extends the literature by positioning dining at a robotic restaurant as an important occasion to showcase the latest technologies to customers. By providing memorable entertainment and educational experiences, customers' technology readiness could be enhanced, making them more willing to try new technologies. Such a focus brings in unique contributions both in literature and practice.

Keywords: Service Robots; Product Level; Experience Economy; Technology Readiness; Robotic Restaurants

1. Introduction

Technological advancement and innovations, changes in customer preferences, increased competition, and the need to offset rising labor costs have driven the implementation of service robots in the hospitality industry (Tuomi et al., 2021). In addition, the outbreak of the COVID-19 pandemic served as a catalyst, further speeding up this process (Wan et al., 2021). Fortune Business Insights (2021) projected that the market size of service robots will reach USD 41.49 billion by 2027, which is more than triple the pre-pandemic figure. Service robots have become increasingly popular over the last decade. In the hotel industry, robots have gradually been used to perform check-in and check-out functions, serving as information hubs, and entertaining customers (Gale & Movhizuki, 2019). In the restaurant industry, fully automatic kitchens and restaurants operated by robots have appeared. For instance, in the US, a restaurant named Spyce in Boston where a fully automated robotic kitchen takes care of the entire cooking process has created an eye-opening experience for people (Somers, 2018), creating social media buzz and inspiring customers to try this innovative dining experience (Bandoim, 2020). In China, the Country Garden Holdings Co. Ltd has opened 6 fully automatic restaurants, where robots take charge of the entire food production and service process, from order taking and processing payment to cooking and delivering food (Davis, 2020).

Known as a “people’s industry” where well-trained employees create and deliver service experiences while involving customers (Kusluvan et al., 2010), hospitality has undergone dramatic changes since the incorporation of service robots in terms of how services are provided. This shift has drawn growing research attention from scholars devoted to identifying how service robots might shape customers’ service experiences, attitudes, and behavioral intentions (e.g., Huang et al., 2021; Lu et al., 2019). Existing research has predominately focused on customers

(Cha, 2020; Lv et al., 2021), with limited research attention given to operators of hospitality organizations or employees (Ma et al., 2021). Scant attention to this aspect limits our understanding of how different service robot adoption/utilization strategies may influence customer experiences differently. For instance, although a restaurant employing a robot only to greet and entertain customers and a restaurant using a robot chef can both be labeled as “robotic restaurants,” the operations costs as well as their influence on customer perception and experience could vary significantly.

And yet, limited studies have examined, from a product/service design perspective, how variations in the application of service robots may influence customer experience (Ma et al., 2021). Examining robots’ applications in restaurants at different product/service layers and different stages of the dining experience is critical—not only for an in-depth understanding of customer experiences but also for restaurant operators to make strategically sound and cost-effective decisions in service experience design and operations. Further, service robots, besides performing assigned duties, embody the mission of showcasing advanced knowledge integrated from the science, engineering, and technology sectors. Can customers gain new knowledge while increasing their curiosity about robotic technologies through their enjoyment of robotic service? Do such experiences enhance customers’ perception of technology readiness (e.g., Parasuraman, 2000), increasing their propensity to embrace new technologies at work and in daily life?

In light of the above, this study aims to explore customer experience with robotic restaurants, building on three main streams of literature: product level theory (Kotler & Keller, 2016), the experience economy model (e.g., Pine & Gilmore, 1999), and technology readiness and acceptance (e.g., Parasuraman, 2000). In particular, the study will investigate whether service robots applied at different product/service levels may influence customer dining experiences differently and whether dining experiences with service robots would affect customers' perceived technology readiness. The study will fill in a literature gap on the topic of service robots, particularly from a product design perspective. The study findings will also have meaningful implications for restaurant operators currently using or planning to use service robots in their operations.

2. Literature Review

In this section, we first introduced the Product Level Theory (Kotler & Keller, 2016), the overarching theory applied in the study, and justified why it is a suitable framework. We then discussed how robots applied at various product/service levels may influence customers' dining experience differently. Finally, building on extensive literature research, we proposed and justified our hypotheses on how robots' applications at different product/service levels may influence customers' educational experience and entertainment experience, and how such experience may influence customers' technology readiness. A conceptual framework summarizing all hypothesized relationships was introduced at the end of the literature review section.

2.1. Theoretical foundations

Smart technologies like artificial intelligence (AI), automation, and robotics have been widely studied in tourism (Tussyadiah, 2020; Yang et al., 2021). As the most dramatic evolution (Mende et al., 2019), robots are introduced building on previous service technologies (Yoganathan et al., 2021). Since their emergence, service robots have been empirically tested in a number of studies including the cuteness of robotic applications (Lv et al., 2022), socialcognitive evaluation (Yoganathan et al., 2021), a robot logistics system (Lee et al., 2021), social crowding and tourist preference (Hou et al., 2021), willingness to pay (Ivanov & Webster, 2021), information sharing and empathy (de Kervenoael et al., 2020), robotics awareness (Li et al., 2019), etc. Specifically, the increasing presence of robots at restaurants is remarkable (Lu et al., 2021). Existing functions of service robots include making food (Zhu & Chang, 2020), greeting and delivering (Tuomi et al., 2021), disinfection or sterilization (Zeng et al., 2021). Research discloses that by adopting robots, restaurants will gain increased sales (Chuah et al., 2021), improved service quality (Morita et al., 2020), positive emotions and behavioral intention (Yoo et al., 2022), etc. In addition, Ma et al. (2021) extended the application of product levels and experience economy model at robotic restaurants. The identified theories, however, have neither tested first-hand data nor their theoretical support for robotic applications at different product/service levels and customers' dining experience. When robots enter the realm of tourism experiences, the robot-assisted experiences at the multiple product levels and experience economy will go beyond what has been theorized in literature thus far. Furthermore, little or no research addresses robot-assisted restaurant customers' technology readiness at multiple product levels.

Because the use of robots in hospitality represents an important service innovation, decisions on which functions can be performed by robots should be made with careful analysis of components and flow of service. According to Kotler and Keller (2016), products/services fall into the core, facilitating, supporting, and augmented categories to serve customers' needs. While the core product level satisfies fundamental needs of consumers, facilitating and supporting elements are necessary for the product/service to function (Kotler & Keller, 2016). Augmented components are also important because they are the extra features that distinguish one product/service from another (Ma et al., 2021). In the case of the restaurant dining experience, while food is a core product/service, greeting services and food ordering belong to the facilitating category. An open kitchen would be an example of an augmented component of the dining experience.

Kotler and Keller's (2016) product level theory has been widely applied in product design and marketing processes, given its strong focus on and alignment with customers' needs. Recent research also suggests that this model is also suitable for either tangible or intangible products, if not a combination of both (e.g., Duan et al., 2018; Ma et al., 2021), in line with the claims of Kotler and Keller (2016). In particular, applications of the model have recently been observed in hospitality and tourism contexts such as hotels (Kosar & Kordić, 2018); wineries (Duan et al., 2018). In addition, this model allows business operators to analyze the profitability of different levels of product/service so that they can invest valuable resources in the most cost-effective components (Hannila et al., 2020). This is particularly relevant to robotic applications in hospitality contexts as using service robots is a big decision involving a significant amount of investment. The decision to use service robots at either all product/service levels or just one or two levels would incur a significantly different cost. Such concern is also reflected in practice. While fully automatic restaurants using service robots to perform all functions are not new, most robotic restaurants still rely on both humans and robots in their daily operations. Yet, there is a shortage of evidence on whether different service robot application models would make a difference in customer experience.

Knowing whether customers' experiences differ due to varied robots' applications models is important, particularly in the era of the experience economy, in which customers are looking for memorable service experiences that involve immersive aesthetic, entertaining, and educational components (Pine & Gilmore, 1999; Lai et al., 2021; Zhang et al., 2021). Further, given that robots applied in service organizations are a relatively new innovation, dining in a robotic restaurant may be considered an ideal occasion to showcase customers the latest technologies. As practicing social responsibilities is an inevitable obligation for today's organizations, we suggest that robotic restaurants may also carry the mission of introducing customers to the latest robotic technologies, providing meaningful experiences with educational and entertainment components to build customers' technology readiness. Below we discuss how different models of robotic applications at different product/service levels may influence customers' perceptions of service experiences, as well as their perceived technology readiness.

2.2. Robotic applications at different product/service levels and educational experience

Robotic technologies have led hospitality services to a unique experience economy in which robots can be used at different stages in service productions and deliveries (Kazandzhieva & Filipova, 2019). Because the experience of being served by robots is considered unique and novel, customers have the potential to possess positive attitudes toward robots (Kazandzhieva & Filipova, 2019) at the core, facilitating, and augmented levels. In terms of applications at different product levels, cooking food in an open kitchen is regarded as a core product. The facilitating product is the service that must be present for customers to enjoy the core product (Kotler et al., 2018) — for instance, hosting customers, taking orders, serving food, paying the bill, etc. The augmented product includes the interaction between customers, servers, and the dining atmosphere (Kotler et al., 2018).

Educational experience, one realm of the experience economy, has been valued in the tourism industries (Duan et al., 2018; Lai et al., 2021; Lee et al., 2020; Mihalache, 2016; Song et al., 2015; Thanh & Kirova, 2018; Zhang et al., 2021). Most of these studies have examined the influence of tourists' perceived educational experience on satisfaction, revisit intention, word of mouth (Lee et al., 2020; Zhang et al., 2021), and functional and emotional values (Lai et al., 2021; Song et al., 2015). References to the educational experience in tourism are salient, although little or no research has been empirically tested the robotic applications at different product/service levels on educational experience in the tourism context. In a robot restaurant, customers' encounter with robots in various tasks can lead to their memorable experiences (Seyitoğlu & Ivanov, 2020). Knowledge is regarded as an important factor for memorable tourism experiences through offering educational experiences and exploration (Kim et al., 2012). The use of robotic technologies in a robot restaurant makes it possible to automate many services and tasks (Xiao & Kumar, 2021) involving different product levels, including core, facilitating, and augmented. Oh et al. (2007) indicated that examples of customers' educational experiences include a themed guestroom at a bed-and-breakfast facility or a cooking demonstration. Educational experience combines with customers' active participation and absorption (Pine & Gilmore, 1999). Thus, customers absorb cooking in the open kitchen (core product); experience greeting, ordering, delivering, etc. (facilitating product); and enjoy singing at a robot restaurant (augmented product). Such experiences may differ at the robot restaurant according to their educational experiences. This leads to the following hypothesis:

H1: Robotic applications at the core (H1a), facilitating (H1b), and augmented (H1c) levels will make a difference in restaurant customers' perceptions of educational experiences.

2.3. Robotic applications at different product/service levels and entertainment experience

Empirical studies have identified the importance of entertainment experience in the tourism industry, including cruise tourism (Hosany & Witham, 2010), wine tourism (Thanh & Kirova, 2018), and ethnic cuisine (Lai et al., 2021). Appealing entertainment offers customers unforgettable memories (Hwang & Han, 2014), which assists the creation of customers' well-being perception (McCabe et al., 2010). The well-being perception refers to customer's positive feelings toward good services (Hwang & Lyu, 2015), and using robots has been suggested as a strategy to generate such positive feelings of customers (Shinde et al., 2022). For example, customers feel that if the robot restaurant was fun, such entertainment experiences would serve a positive memory which improves their service quality. Thus, it would be fruitful to determine the entertainment experience of robot restaurants and assess customers' perception, which still requires research investigatioins despite the increasing trends of adopting robots at restaurants (Hwang et al., 2020).

Entertainment experience requires that the offerings of experience occupy and catch individuals' attention and readiness (Oh et al., 2007), then combine with passive participation and absorption (Pine & Gilmore, 1999). Wine and food festivals are central to entertaining guests (Axelsen & Swan, 2010) by providing food and wine demonstrations (sometimes in tandem), service or product prices, and concerts and music (Thanh & Kirova, 2018). A robot can be used not only to deliver the food but also to host and entertain guests in the restaurants (Seyitoğlu & Ivanov, 2020), thus activating the core, facilitating, and augmented product levels. Robots, as representatives of cutting-edge technology, can delight customers' dining experiences by performing various roles, including chef, deliverer, and entertainer (Go et al., 2020). Therefore, robot applications offer an entertainment experience through observation of cooking food (core product), hosting and delivering (facilitating product), and entertaining customers at a robot restaurant (augmented product), all of which amounts to being entertained differently from the normal routine. Based on the above, we propose:

H2: Robotic applications at the core (H2a), facilitating (H2b), and augmented (H2c) levels will make a difference in restaurant customers' perceptions of entertainment experiences.

2.4. Technology readiness

Technology readiness, as defined by Parasuraman (2000), is "people's propensity to embrace and use new technologies for accomplishing goals in home life and at work" (p. 308). Parasuraman and Colby (2015) then developed TRI 2.0, a multi-dimensional scale to measure technology readiness. Conceptualizing technology readiness as a second-order concept, Parasuraman and Colby (2015) used dimensions of optimism (i.e., positive attitude and belief in technology), innovativeness (i.e., tendency of a user to be a thought leader in using technology), discomfort (i.e., being overwhelmed by technology and feeling unable to control it), and insecurity (i.e., distrust in technology and worry about the harmful consequences thereof) to construct the TRI 2.0 scale. Through gaining use experiences with technology-based products and services (e.g., online booking, ride-sharing apps, social media, or mobile payment) (Shin et al., 2021; Verma et al., 2012; Wang et al., 2016), tourists and hospitality customers have been examined through empirical evidence regarding the potential to gain technology readiness. In line with this phenomenon, we propose that restaurant customers' robot-assisted experiences would support the formation of their technology readiness.

We further propose that the two domains of robot-assisted experiences—education and entertainment—would assist customers in developing technology readiness. From a learning perspective, the educational experience offers opportunities for customers to learn what a robot-assisted restaurant experience would be, understand what robots can do at restaurants, and realize what to expect when having robots attend to work tasks at restaurants (Byrd et al., 2021; Ma et al., 2021). The knowledge-based information gathered during a robot-assisted restaurant experience prepares customers to welcome future technology-assisted tasks and opportunities. On the other hand, from an entertainment perspective, robot-assisted restaurant experiences would bring emotional delights and recreational opportunities to customers, making the customer happy and ready to welcome technology wholeheartedly. Examples of such an approach include customers' perceived fun and the hedonic characteristics (Choi et al., 2019), coolness (Cha, 2020), and cuteness (Lv et al., 2021) attributed to service robots. Taken together, we propose:

H3: Restaurant customers' perceptions of (H3a) educational and (H3b) entertainment experiences with service robots will influence their perceptions of technology readiness.

2.5. Moderating effects of risk taking and social curiosity

For the formation of technology readiness, risk taking and social curiosity are proposed as the moderators. Risk taking is a type of personal factor which refers to the extent of an individual to take risks (Dawson et al., 2011). Social curiosity refers to the tendency of an individual to acquire information based on how others feel, think, and behave (Kashdan et al., 2018). Previous empirical studies on technology readiness found that users' risk taking tendencies (Kopalle et al., 2020) and curiosity (Cheng & Guo, 2021; Cruz-Cárdenas et al., 2021) are associated with high levels of technology readiness. Technology users with high risk taking tendencies are more likely to try new technology experiences and stay open-minded to see the positive sides of new technological applications (Kopalle et al., 2020), and therefore would gain more benefits on the formation of technology readiness. On the other hand, curious users are interested to try new things and then gain readiness for new technological applications (Cheng & Guo, 2021; Cruz-Cárdenas et al., 2021). This study highlights social curiosity (Kashdan et al., 2018) because dining at restaurants allows customers to observe how other customers interact with restaurant robots, which may further motivate their interest to interact and learn from the robotic interactions and built their technology readiness. Therefore, the positive relationships between restaurant customers' robot-assisted experiences and their technology readiness would be strengthened by their extent of being risk taking and social curiosity. Based on the above, we propose:

H4. The extent of being risk taking moderates the relationship between restaurant customers' perceived educational experience and technology readiness. The relationship is stronger when risk taking is high than when risk taking is low.

H5. The extent of being risk taking moderates the relationship between restaurant customers' perceived entertainment experience and technology readiness. The relationship is stronger when risk taking is high than when risk taking is low.

H6. Restaurant customers' social curiosity moderates the relationship between their perceived educational experience and technology readiness. The relationship is stronger when social curiosity is high than when social curiosity is low.

H7. Restaurant customers' social curiosity moderates the relationship between their perceived entertainment experience and technology readiness. The relationship is stronger when social curiosity is high than when social curiosity is low.

2.6 The research framework

Figure 1 shows the research framework of this study. Building on product level theory (Kotler & Keller, 2016), we propose facilitating, core, and augmented product levels to examine the differences between customers' interactions with robots and human employees at restaurants. Further, based on experience economy (Pine & Gilmore, 1999), we identify educational and entertainment experiences as the two major domains in robot-assisted experiences enhanced through interactions at the abovementioned product levels. Through educational and entertainment experiences, we propose that customers can gain technology readiness (Parasuraman, 2000). Meanwhile, customers' frequency of visiting robotic restaurants would strengthen their technology readiness.

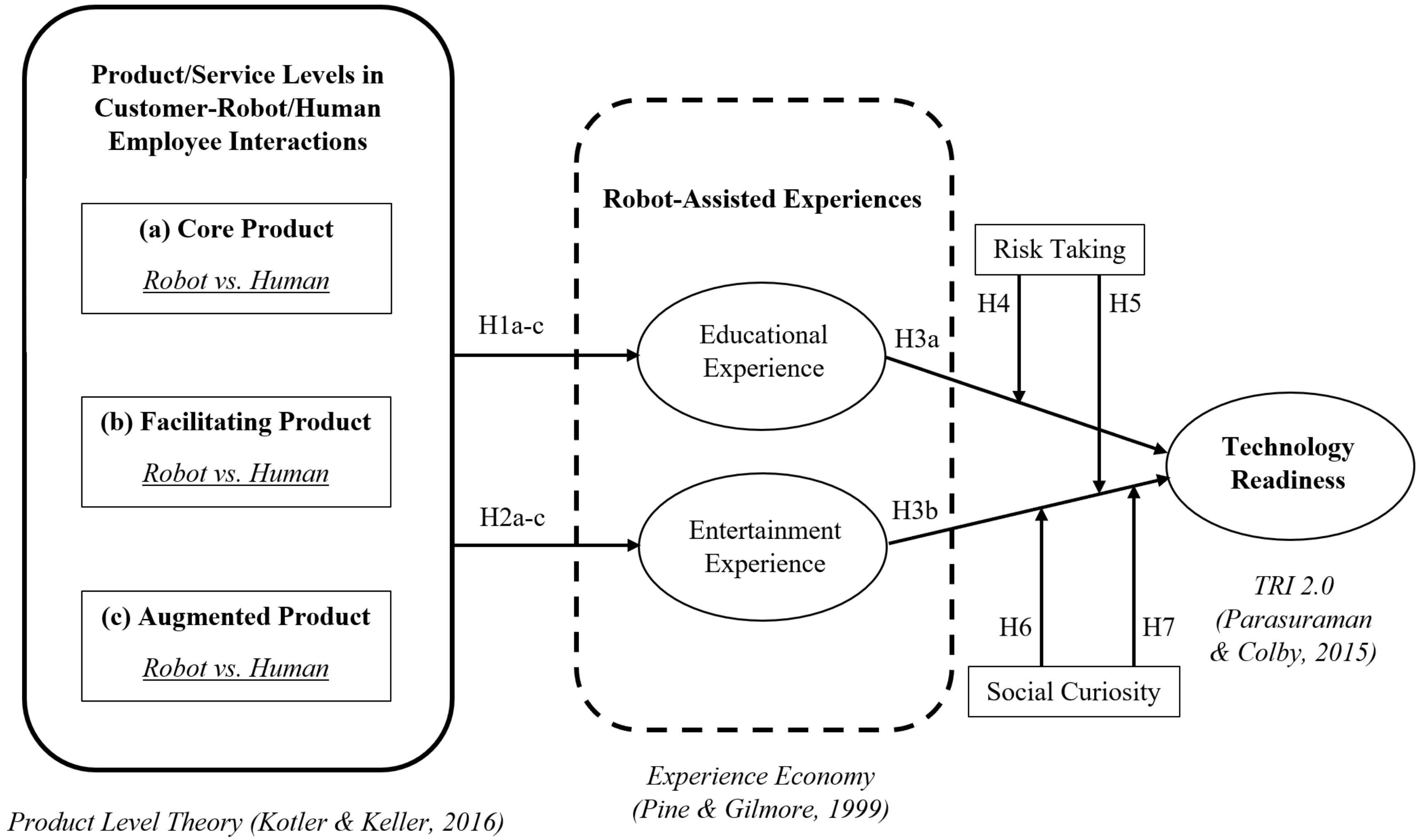


Figure 1. Research framework

3. Method

We conducted two between-subjects 2 (core product: human vs. robot) x 2 (facilitating product: human vs. robot) x 2 (augmented product: human vs. robot) experiments to test the effects of three independent variables on consumers' perceived experience. Eight versions of dining experience scenarios were developed for both studies. The context of Study 1 was a mid-priced casual Chinese restaurant in China, and Study 2 was a mid-priced restaurant in a theme park in China (see Appendix 1). To minimize the confounding effect, such as the effect of meal prices and types of restaurant on consumer perception, we selected a mid-priced casual restaurant, rather than cheap fast-food or expensive fine-dining restaurants.

3.1 Measurement

All measurements of constructs were developed from the existing literature using a 7-point Likert scale ranging from 1 (strongly disagree) to 7 (strongly agree). Majority of the constructs in Studies 1 and 2 were the same. For example, in terms of consumers' perceived experience, two dimensions of education and entertainment from the experience economy scale (Oh et al., 2007) were considered appropriate for this project. More specifically, four items were used to measure educational experience for all of the surveys. However, four items to assess entertainment experience were slightly modified to fit three types of scenarios, including 1) one scenario using robots for all three levels of products, 2) one scenario having human chefs/servers for all three levels of products, and 3) six scenarios having a mix of both robots and humans across product levels. We developed the scale of consumers' technology readiness after dining in the restaurant from the technology readiness index (Parasuraman & Colby, 2015). We developed two types of measurement for technology readiness to adapt to the context of scenarios, including seven scenarios involving robots in the restaurant and one scenario in which humans fulfill every function of the restaurant. We also included two different moderators for both studies. In Study 1, we used two items to measure risk taking (Dawson et al., 2011). In Study 2, we used three items to measure social curiosity (Kashdan et al., 2018). The measure items, factor loadings, and reliability scores are shown in Appendix 2. All measure items were originally developed in English from English literature and were translated into Chinese by the research team, all of whom are fluent in English and Chinese.

3.2 Data collection

The experimental data was gathered via a leading online marketing research firm, Wenjuanxing, in China. A large number of studies acknowledged that this online marketing research firm collects reliable and valid data, since it adopts the random sampling approach to distribute online surveys to its database of 2.6 million consumers and the firm implements multiple measures to filter reliable and valid responses (Song et al., 2021; Wang et al., 2018). A web link including the scenario description and the corresponding questionnaire was sent to the online panel members to invite qualified subjects to complete the survey. Each participant was randomly placed to one of the eight versions. After reading the scenario description, participants were asked to assess the scenarios and answer general questions such as demographic background and frequency of dining in robotic restaurants. As shown in Table 1, altogether, 690 Chinese participants were involved in both experiments. Below is the leading demographic category: aged 21-30, married, being female, held an undergraduate degree, and white-collar workers. The most popular monthly income in Study 1 is RMB 7000-9999, whereas in Study 2 is

RMB 10000 and above. More than half of participants in both studies visited robotic restaurants 1-5 times. Using G*Power, we entered the criteria of a medium effect size (f=0.25), an a err prob of 0.05, and a power of 0.95 (G*Power, 2021) to conclude that 270 is the minimum sample size for each experiment.

Table 1. Participants' profile

Variable		**Study 1** (Total sample size: 378)	**Study 2** (Total sample size: 312)
Age	18-20	12 (3.2%)	5 (1.6%)
	21-30	164 (43.4%)	151 (48.4%)
	31-40	158 (41.8%)	128 (41.0%)
	41-50	37 (9.8%)	17 (5.4%)
	51-60	7 (1.9%)	9 (2.9%)
	61 and above	0 (0%)	2 (.6%)
Marital status	Single	84 (22.2%)	51 (16.3%)
	Married	287 (75.9%)	260 (83.3%)
	Divorced	3 (.8%)	1 (.3%)
	Other	4 (1.1%)	0 (0%)
Gender	Male	168 (44.4%)	115 (36.9%)
	Female	210 (55.6%)	197 (63.1%)
Education	High school or below	11 (2.9%)	5 (1.6%)
	College	36 (9.5%)	25 (8.0%)
	Undergraduate	284 (75.1%)	259 (83.0%)
	Postgraduate	47 (12.4%)	23 (7.4%)
Occupation	Governmental officer	18 (4.8%)	17 (5.4%)
	Entrepreneur	45 (11.9%)	43 (13.8%)
	Professional	70 (18.5%)	45 (14.4%)
	Private business owners	19 (5.0%)	5 (1.6%)
	White collar	173 (45.8%)	167 (53.5%)
	Salesperson	17 (4.5%)	11 (3.5%)
	Self-employed	8 (2.1%)	7 (2.2%)
	Students	23 (6.1%)	12 (3.8%)
	Retired	0 (0%)	1 (.3%)
	Others	5 (1.3%)	4 (1.3%)
Personal annual income	Less than 3000	29 (7.7%)	14 (4.5%)
	3000~4999	32 (8.5%)	29 (9.3%)
	5000~6999	79 (20.9%)	50 (16.0%)

	7000~9999	121 (32.0%)	99 (31.7%)
	10000 and above	117 (31.0%)	120 (38.5%)
Times of visiting robotic restaurants	0	126 (33.3%)	67 (21.5%)
	1-5	221 (58.5%)	203 (65.1%)
	6-10	28 (7.4%)	35 (11.2%)
	More than 10	3 (.8%)	7 (2.2%)

3.3 Data analysis

Two sets of data analysis were implemented to test the hypotheses. First, the effects of independent variables on consumers' perceived educational and entertaining experiences were tested using a three-way analysis of covariance (ANCOVA). Because consumers' demographic characteristics and prior experience influence their perception and assessment of service experiences (Wu et al., 2014), we treated demographic variables and frequency of dining in robotic restaurants as control variables in running the ANCOVA. Second, the relationship between educational, entertaining experiences, and technology readiness as well as the moderation part of the model was conducted using Haye's PROCESS model.

4. Results of Study 1

4.1 Manipulation check

Experimental manipulations of the three independent variables were successful. In terms of the restaurant's core product, participants in the robot chef condition said, "Several robots were cooking in the open kitchen" at rates significantly higher than those allocated in the human chef condition ($M_{Robot} = 6.82 > M_{Human} = 1.37$; $t(376) = 81.073$; $p < .001$). In terms of the facilitating product, participants in the robot server condition rated the item of "robot, as the server, greeted, led you to your table, took the order, payment, and food delivery to your table" significantly higher than the participants in the human server condition ($M_{Robot} = 6.75 > M_{Human}$

= 1.23; t(376) = 109.437; p < .001). Regarding the augmented product in the restaurant, the participants in the robot condition agreed more on "robots, as servers, sang a birthday song to a group of customers near your table in the restaurant" than those in the human condition (M_{Robot} = 6.80 > M_{Human} = 1.82; t (376) = 36.638; p < .001).

4.2 Main effect and interaction effect on educational experience

As shown in Table 2, among all control variables, only income influenced consumers' educational experience (F [1, 363] = 4.755; p < .05). As expected, all three product levels significantly affected consumers' educational experience. In particular, the use of robots in all three product levels contributed more positively to consumers' educational experience than the use of human beings. For instance, robots in the core products condition generated a higher level of educational experience than human beings in the core products condition ($M_{Robot\text{-}Core}$ = 5.82 > $M_{Human\text{-}Core}$ = 4.89; F [1, 363] = 84.692; p < .001; effect size: .189). Similarly, robots in the facilitating product condition contributed more to consumers' educational experience than humans in the same condition ($M_{Robot\text{-}Facilitating}$ = 5.95 > $M_{Human\text{-}Facilitating}$ = 4.76; F [1, 363] = 134.749; p < .001; effect size: .271). Likewise, robots in the augmented product significantly enhanced consumers' educational experience ($M_{Robot\text{-}Augmented}$ = 5.70 > $M_{Human\text{-}Augmented}$ = 5.01; F [1, 363] = 46.361; p < .001; effect size: .113). Thus, H1a-c are all supported.

Table 2. ANCOVA results on consumers' educational experience (Study 1)

Sources	***df***	**F**	**Sig.**	**Effect size**
Control variables				
Age	1	.030	.862	.000
Marital status	1	.039	.844	.000
Gender	1	1.501	.221	.004
Education	1	1.863	.173	.005
Job	1	.012	.912	.000

Income	1	4.755	.030	.013
Frequency of dining in robotic restaurants	1	1.258	.263	.003
Independent variables				
Facilitating	1	134.749	.000	.271
Core	1	84.692	.000	.189
Augmented	1	46.361	.000	.113
Facilitating * Core	1	66.032	.000	.154
Facilitating * Augmented	1	36.315	.000	.091
Core * Augmented	1	40.282	.000	.100
Facilitating * Core * Augmented	1	40.133	.000	.100
Error	363			

This study also witnessed three two-way interaction effects and one three-way interaction effect on consumers' educational experience. The three two-way interaction effects include a two-way interaction effect between core and facilitating products (F [1, 363] = 66.032, p < .001; effect size:.154), a two-way interaction effect between facilitating and augmented products (F [1, 363] = 36.315; p < .001; effect size: .091), and a two-way interaction effect between core and augmented products (F [1, 363] = 40.282; p < .001; effect size: .100). A three-way interaction effect between core, facilitating, and augmented products on consumers' educational experience was observed (F [1, 363] = 40.133; p < .001; effect size: .100).

To better interpret the interaction effects, this study adopted the suggestions by some scholars (Song et al., 2021) in that only the three-way interaction effect should be reported if both the two- and three-way interaction effects are confirmed. According to previous studies (Song et al., 2021), the dataset needs to be divided into separate parts based on one of the independent variables. As core products are normally considered the key offering in restaurants, this study separated the dataset based on two types of core products: robot chefs and human chefs. Then, two separate two-way ANCOVAs were conducted with the dataset of either robot chefs or human chefs. In terms of the robot chef condition, there was no two-way interaction effect ($F [1, 189] = .002$, $p = .962$, effect size: .000). As shown in Figure 2, in the situation of robot facilitation, there was no difference between robot- and human-oriented augmented products ($M_{\text{Robot augmented – Robot facilitating}} = 6.03$; $M_{\text{Human augmented – Robot facilitating}} = 5.99$; $F [1, 189] = .065$, $p = .799$). Similarly, in the situation of human facilitation, there was also no difference between robot-oriented and human-oriented augmented product ($M_{\text{Robot augmented – Human facilitating}} = 5.67$; $M_{\text{Human augmented – Human facilitating}} = 5.63$; $F [1, 189] = .032$, $p = .859$).

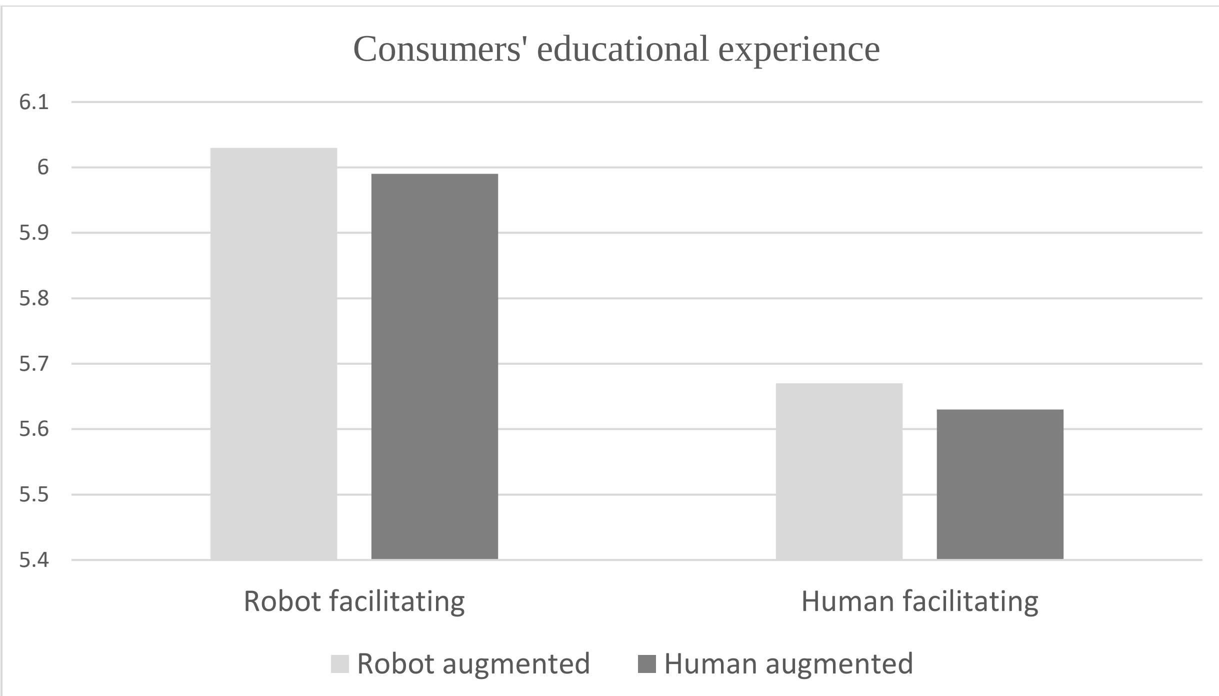


Figure 2. Interaction effect between facilitating product and augmented product on consumers' educational experience in the robot core product condition (Study 1)

While analyzing the core product dataset created by human chefs, a significant two-way interaction effect ($F [1, 167] = 49.805$, $p < .001$, effect size: .230) was confirmed. As depicted in Figure 3, the results demonstrated that when the facilitating product was delivered by human beings, there was a significant difference in that the robot-augmented product generated a significantly higher mean value of educational experience than the human augmented product ($M_{\text{Robot augmented – Human facilitating}} = 5.16$; $M_{\text{Human augmented – Human facilitating}} = 2.59$; $F [1, 167] = 118.364$, $p < .001$). However, when the robot facilitating product category was used, consumers perceived the mean value of educational experience to be similar between robot- and human-oriented augmented products ($M_{\text{Robot augmented – Robot facilitating}} = 5.94$; $M_{\text{Human augmented – Robot facilitating}} = 5.82$; $F [1, 167] = .241$, $p = .624$).

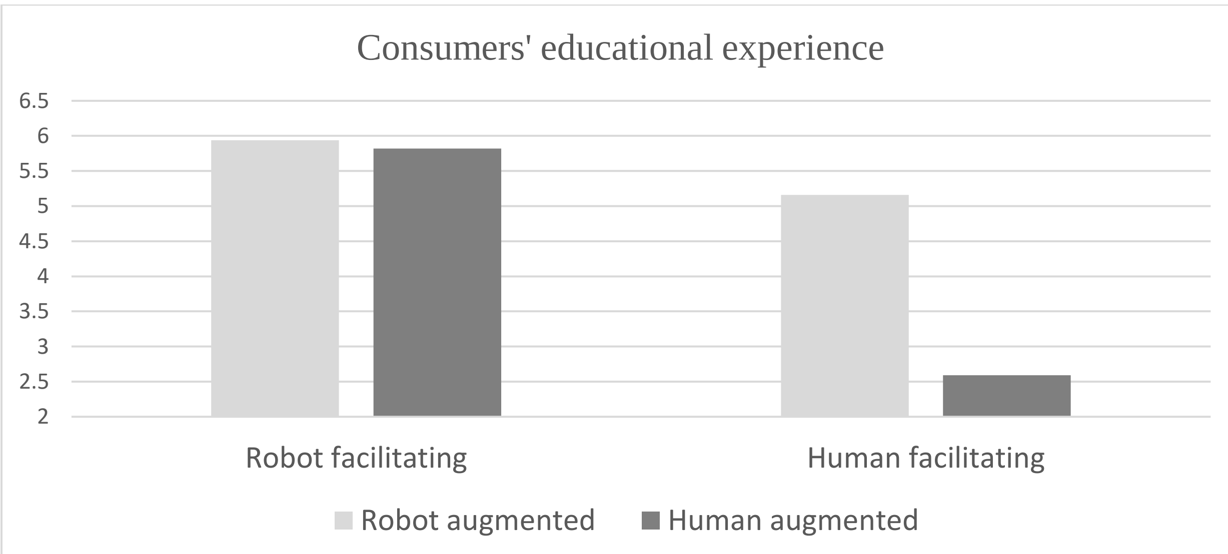


Figure 3. Interaction effect between facilitating product and augmented product on consumers' educational experience in the human core product condition (Study 1)

4.3 Main effects and interaction effects on entertainment experience

According to Table 3, no control variables affected consumers' entertaining experience. Contrary to our expectations, there were no main effects from core, facilitating, and augmented products on consumers' entertaining experience. Thus, H2a-c are all rejected. However, we confirmed a two-way interaction effect between facilitating and augmented products on consumers' entertainment experience ($F [1, 363] = 9.308$; $p < .01$). As shown in Figure 4, while using a robot as an augmented provider, there was a significant difference between robot-oriented and human-oriented facilitating products ($M_{\text{Robot augmented – robot facilitating}} = 5.87$; $M_{\text{Robot augmented – human facilitating}} = 5.54$; $F [1, 363] = 7.124$, $p = .008$). While using a human as an augmented provider, there was no significant difference between robot-oriented and human-oriented facilitating products ($M_{\text{Human augmented – robot facilitating}} = 5.58$; $M_{\text{Human augmented – human facilitating}} = 5.78$; $F [1, 363] = 2.655$, $p = .104$).

Table 3. ANCOVA results on consumers' entertainment experience (Study 1)

Sources	***df***	**F**	**Sig.**	**Effect size**
Control variables				
Age	1	2.440	.119	.007
Marital status	1	.373	.542	.001
Gender	1	.000	.998	.000
Education	1	.440	.507	.001
Job	1	.817	.367	.002
Income	1	2.818	.094	.008
Frequency of dining in robotic restaurants	1	3.328	.069	.009
Independent variables				
Facilitating	1	.667	.415	.002
Core	1	.010	.920	.000
Augmented	1	.064	.800	.000
Facilitating * Core	1	.845	.359	.002
Facilitating * Augmented	1	9.308	.002	.025
Core * Augmented	1	2.692	.102	.007
Facilitating * Core * Augmented	1	.770	.381	.002
Error	363			

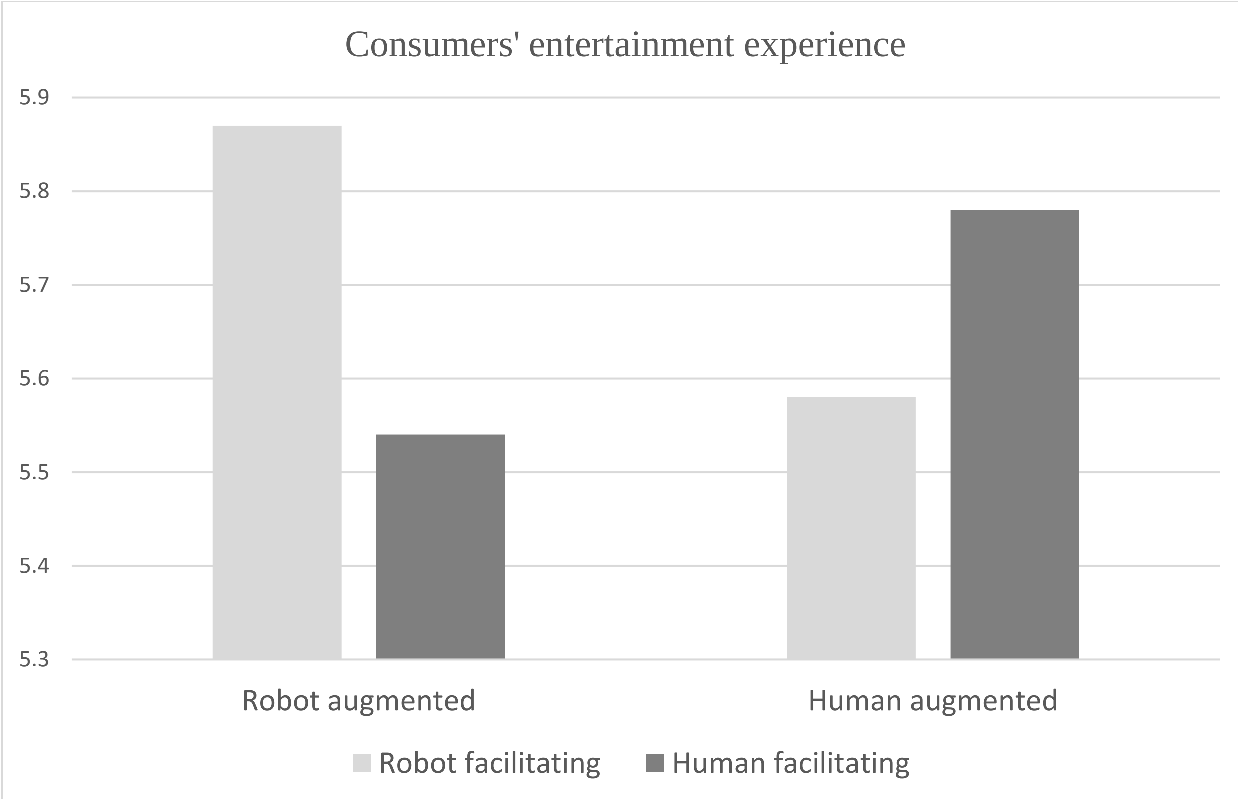


Figure 4. Interaction effect between facilitating product and augmented product (Study 1)

4.4 Moderating effects of risk taking

We conducted the PROCESS to test the relationship between educational experience, entertaining experience, and consumers' technology readiness, and to check whether risk taking was a moderator. Demographic variables (e.g., age, gender, marital status, occupation, education, and income) and frequency of dining in robotic restaurants were treated as control variables in the analysis. Model 4 results demonstrated that none of the control variables affected technology readiness. As expected, both educational (coeff = .537; $p < .001$; 95% CI .490 to .583) and entertainment experience (coeff = .123; $p < .005$; 95% CI .038 to .207). Therefore, Hypotheses H3a and H3b are accepted.

In terms of the moderating effect of risk taking, Table 4 show that risk taking was the moderator between educational experience and consumers' technology readiness (F [1, 365] =

10.302; p < .005; coeff = .061; 95% CI .024 to .098). More specifically, the effect of educational experience on technology readiness is higher for the participants with high level of risk taking than those with low level. There was no moderating effect of risk taking on the relationship between entertainment experience and technology readiness (F [1, 365] = .170; p = .681; coeff = .012; 95% CI -.047 to .072). Thus, H4 is accepted and H5 is rejected.

Table 4. Moderation results of risk taking

Conditional effects of educational experience on consumers' technology readiness	**Effect (se)**	***p***	**LL 95% CI**	**UL95% CI**
Low level (Mean=4)	.461 (.034)	.000	.394	.529
Medium level (Mean=5.5)	.552 (.024)	.000	.505	.599
High level (Mean=6.5)	.613 (.033)	.000	.549	.677

5. Results of Study 2

5.1 Manipulation check

With same checking items of Study 1, experimental manipulations of the three independent variables in Study 2 were successful. In terms of the core product, participants in the robot chef condition rated significantly higher than those allocated in the human chef condition ($M_{Robot} = 6.84 > M_{Human} = 1.29$; t(310) = 93.305; p < .001). In terms of the facilitating product, participants in the robot server condition rated significantly higher than the participants in the human server condition ($M_{Robot} = 6.79 > M_{Human} = 1.27$; t (310) = 93.305; p < .001). Regarding the augmented product, the participants in the robot condition agreed more than those in the human condition ($M_{Robot} = 6.74 > M_{Human} = 1.23$; t (310) = 107.638; p < .001).

5.2 Main effect and interaction effect on educational experience

As shown in Table 5, among all control variables, only education influenced consumers' educational experience ($F [1, 297] = 5.562$; $p < .05$). Similar to Study 1, all three product levels significantly affected consumers' educational experience. In particular, the use of robots in all three product levels contributed more positively to consumers' educational experience than the use of human beings. For instance, robots in the core products condition generated a higher level of educational experience than human beings in the core products condition ($M_{\text{Robot-Core}} = 5.84 > M_{\text{Human-Core}} = 5.29$; $F [1, 297] = 30.398$; $p < .001$; effect size: .093). Similarly, robots in the facilitating product condition contributed more to consumers' educational experience than humans in the same condition ($M_{\text{Robot-Facilitating}} = 5.93 > M_{\text{Human-Facilitating}} = 5.21$; $F [1, 297] = 50.714$; $p < .001$; effect size: .146). Likewise, robots in the augmented product significantly enhanced consumers' educational experience ($M_{\text{Robot-Augmented}} = 5.81 > M_{\text{Human-Augmented}} = 5.32$; $F [1, 297] = 23.204$; $p < .001$; effect size: .072). Thus, H1a-c are all supported.

Table 5. ANCOVA results on consumers' educational experience (Study 2)

Sources	***df***	**F**	**Sig.**	**Effect size**
Control variables				
Age	1	.669	.414	.002
Marital status	1	.894	.345	.003
Gender	1	.232	.631	.001
Education	1	5.562	.019	.018
Job	1	.160	.689	.001
Income	1	.000	.985	.000
Frequency of dining in robotic restaurants	1	2.189	.140	.007
Independent variables				
Facilitating	1	50.714	.000	.146
Core	1	30.398	.000	.093
Augmented	1	23.204	.000	.072
Facilitating * Core	1	31.581	.000	.096
Facilitating * Augmented	1	18.850	.000	.060
Core * Augmented	1	18.721	.000	.059

Facilitating * Core * Augmented	1	21.834	.000	.068
Error	297			

This study also witnessed three two-way interaction effects and one three-way interaction effect on consumers' educational experience. The three two-way interaction effects include a two-way interaction effect between core and facilitating products (F [1, 297] = 31.581, p < .001; effect size: .096), a two-way interaction effect between facilitating and augmented products (F [1, 297] = 18.850; p < .001; effect size: .060), and a two-way interaction effect between core and augmented products (F [1, 297] = 18.721; p < .001; effect size: .059). A three-way interaction effect between core, facilitating, and augmented products on consumers' educational experience was observed (F [1, 297] = 21.834; p < .001; effect size: .068).

Similar to Study 1, we separated the dataset based on two types of core products: robot chefs and human chefs to conduct two separate two-way ANCOVAs. In terms of the robot chef condition, there was no two-way interaction effect (F [1, 142] = .031, p = .860, effect size: .000). As shown in Figure 5, in the situation of robot facilitation, there was no difference between robot- and human-oriented augmented products ($M_{\text{Robot augmented – Robot facilitating}}$ = 5.97; $M_{\text{Human augmented – Robot facilitating}}$ = 5.88; F [1, 142] = .301, p = .584). Similarly, in the situation of human facilitation, there was also no difference between robot-oriented and human-oriented augmented product ($M_{\text{Robot augmented – Human facilitating}}$ = 5.79; $M_{\text{Human augmented – Human facilitating}}$ = 5.74; F [1, 142] = .096, p = .758).

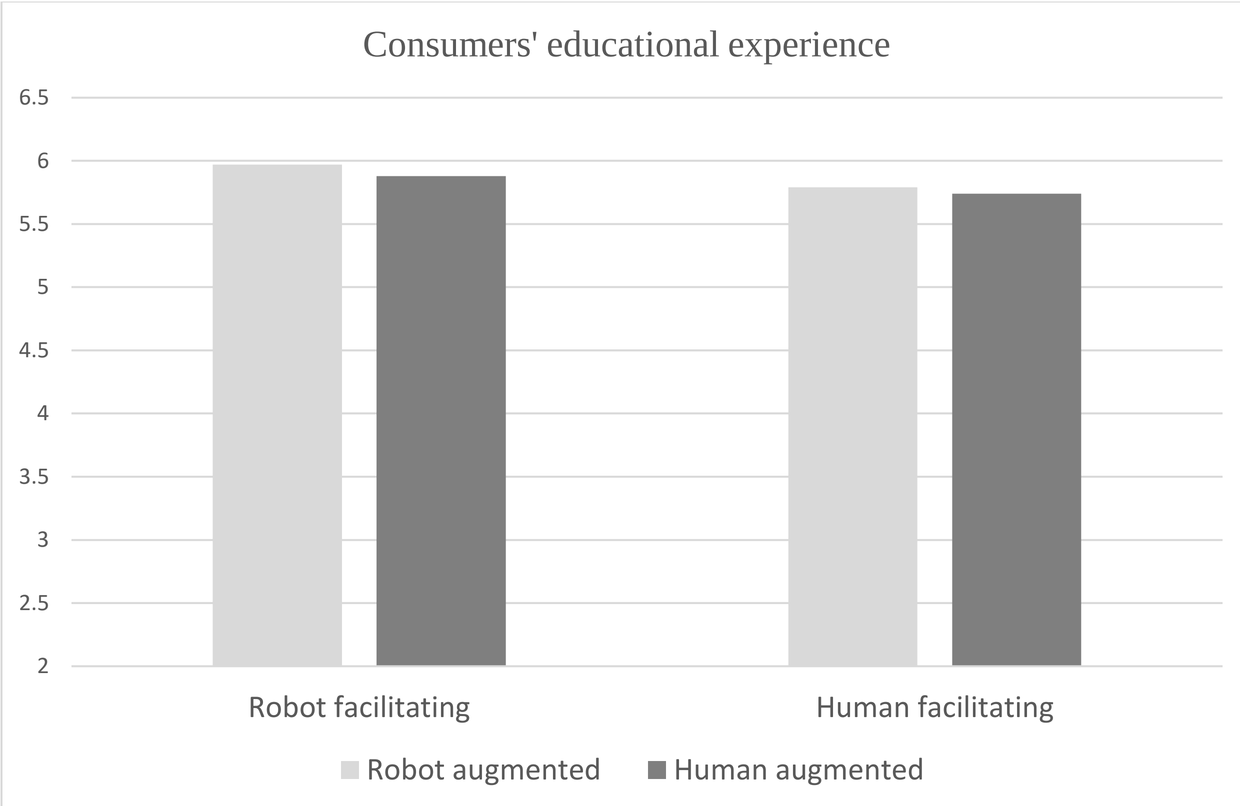


Figure 5. Interaction effect between facilitating product and augmented product on consumers' educational experience in the robot core product condition (Study 2)

While analyzing the core product dataset created by human chefs, a significant two-way interaction effect (F [1, 148] = 28.641, $p < .001$, effect size: .162) was confirmed. More specifically, in the condition of human facilitation, there was a significant difference between robot-oriented and human-oriented augmented products (F [1, 148] =59.841, $p < .001$). As depicted in Figure 6, the results demonstrated that when the facilitating product was delivered by human beings, there was a significant difference in that the robot-augmented product generated a significantly higher mean value of educational experience than the human augmented product ($M_{\text{Robot augmented – Human facilitating}} = 5.56$; $M_{\text{Human augmented – Human facilitating}} = 3.73$). However, in the condition of robot facilitation, there was no significant difference of consumers perceived mean value of educational experience between robot- and human-oriented augmented products ($M_{\text{Robot augmented – Robot facilitating}} = 5.95$; $M_{\text{Human augmented – Robot facilitating}} = 5.91$; $F[1, 148] = .036$, $p = .850$).

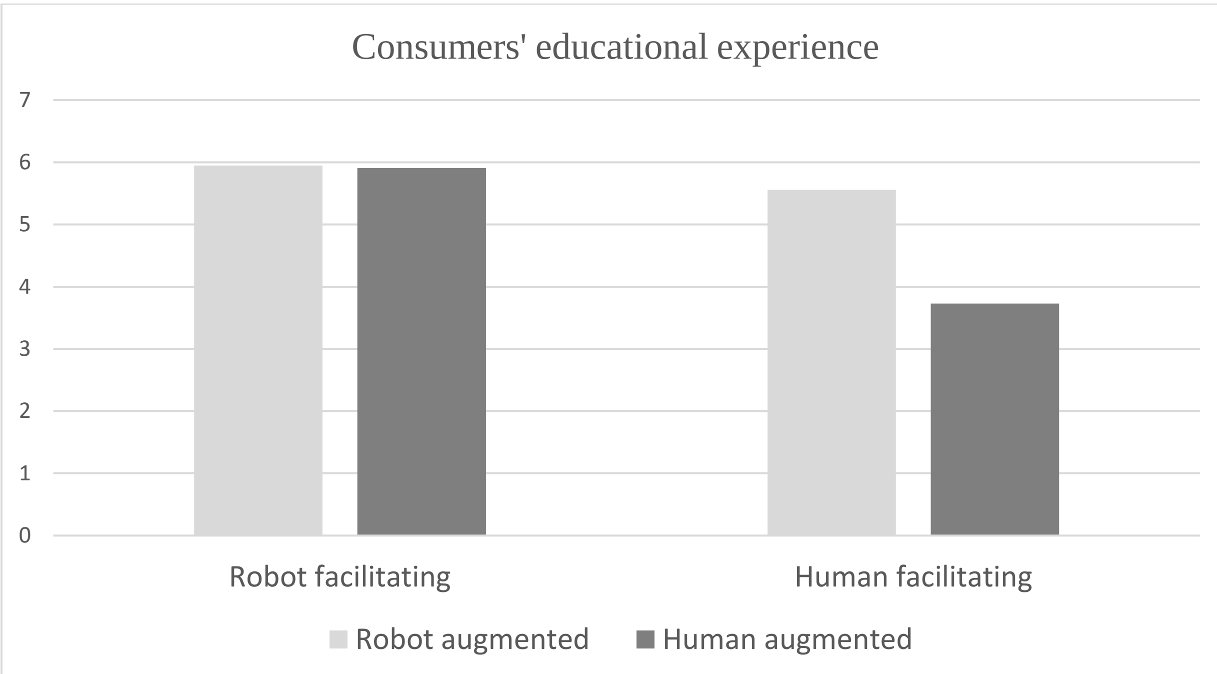


Figure 6. Interaction effect between facilitating product and augmented product on consumers' educational experience in the human core product condition (Study 2)

5.3 Main effects and interaction effects on entertainment experience

According to Table 6, contrary to our expectations, there were no main effects from core, facilitating, and augmented products on consumers' entertaining experience. Thus, H2a-c are all rejected. However, we confirmed a two-way interaction effect between facilitating and augmented products on consumers' entertainment experience ($F[1, 297] = 7.804$; $p < .01$). As shown in Figure 7, while using a robot as an augmented provider, there was no significant difference between robot-oriented and human-oriented facilitating products ($M_{\text{Robot augmented – robot facilitating}} = 5.77$; $M_{\text{Robot augmented – human facilitating}} = 5.56$; $F[1, 297] = 2.881$, $p = .091$). While using a human as an augmented provider, there was a significant difference between robot-oriented and human-oriented facilitating products ($M_{\text{Human augmented – robot facilitating}}$ = 5.66; $M_{\text{Human augmented – human facilitating}}$ = 5.94; F [1, 297] = 5.012, p = .026).

Table 6. ANCOVA results on consumers' entertainment experience (Study 2)

Sources	***df***	**F**	**Sig.**	**Effect size**
Control variables				
Age	1	.677	.411	.002
Marital status	1	.366	.546	.001
Gender	1	3.905	.049	.013
Education	1	.333	.564	.001
Job	1	.241	.624	.001
Income	1	.022	.881	.000
Frequency of dining in robotic restaurants	1	4.317	.039	.014
Independent variables				
Facilitating	1	.181	.671	.001
Core	1	3.307	.070	.011
Augmented	1	2.456	.118	.008
Facilitating * Core	1	.615	.434	.002
Facilitating * Augmented	1	7.804	.006	.026
Core * Augmented	1	.267	.606	.001
Facilitating * Core * Augmented	1	.467	.495	.002
Error	297			

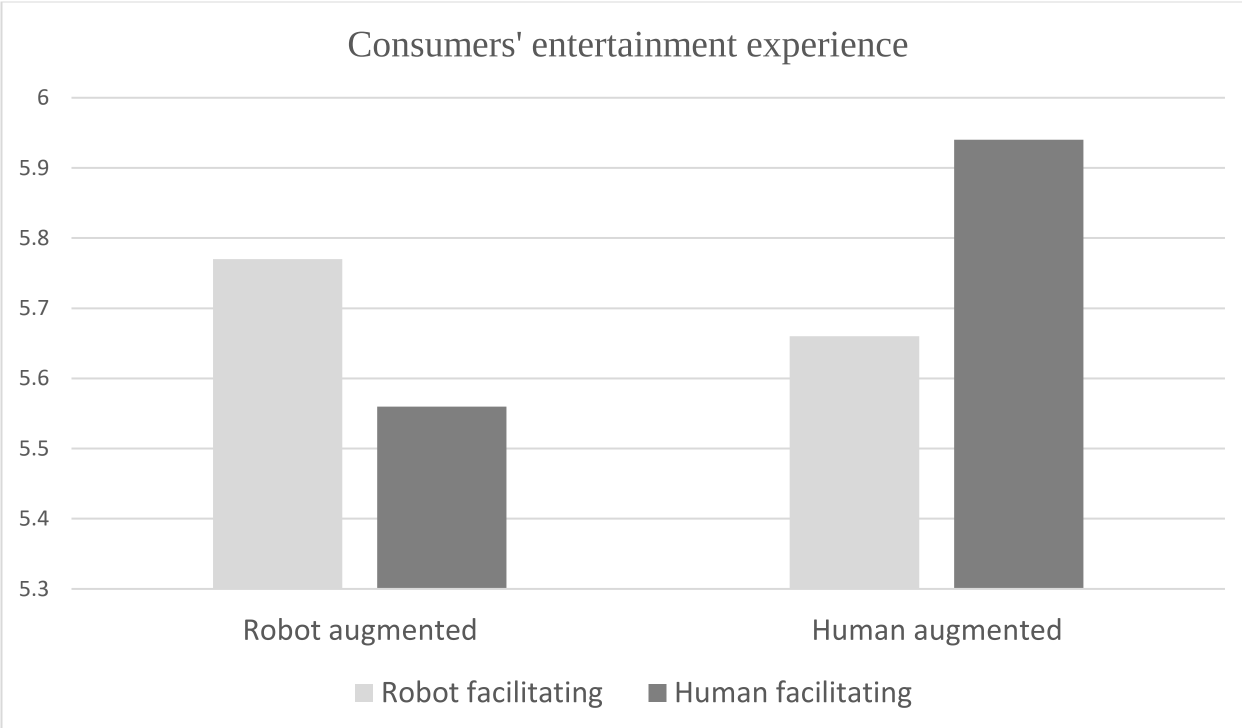


Figure 7. Interaction effect between facilitating product and augmented product (Study 2)

5.4 Moderating effects of social curiosity

Similar to study 1, we conducted the PROCESS to test the relationship between educational experience, entertaining experience, and consumers' technology readiness, as well as whether social curiosity was a moderator. Demographic variables (e.g., age, gender, marital status, occupation, education, and income) and frequency of visiting robotic restaurants were treated as control variables. The results demonstrated that three control variables affected technology readiness. For instance, age (coeff = .139; $p < .01$, 95% CI .042 to .236), income (coeff = .136; $p < .001$, 95% CI .061 to .210), and frequency of dining in robotic restaurants (coeff = .139; $p < .05$, 95% CI .023 to .255). As expected, educational experience significantly influenced consumers' technology readiness (coeff = .683; $p < .001$, 95% CI .617 to .749). Surprisingly, entertainment experience did not affect consumers' technology readiness (coeff

= .082; p = .094; 95% CI -.014 to .178). Therefore, Hypotheses H3a is accepted and H3b is rejected.

Social curiosity was the moderator between educational experience and consumers' technology readiness (F[1, 299] = 22.457; p < .001; coeff = .148; 95% CI .087 to .210). As shown in Table 7, the effect of educational experience on technology readiness is higher for the participants with high level of social curiosity than those with low level. But, social curiosity partially moderated the relationship between entertainment experience and technology readiness (F[1, 299] = 4.971; p < .05; coeff = -.088; 95% CI -.166 to -.010). As shown in Table 7, the effect of entertainment experience on technology readiness only worked for the participants with low level of social curiosity. However, the effect didn't work for the participants with medium and high level of social curiosity. Thus, H6 is accepted and H7 is rejected.

Table 7. Moderation results of social curiosity

Effects by Levels	**Effect (se)**	***p***	**LL 95% CI**	**UL95% CI**
Conditional effects of educational experience on consumers' technology readiness				
Low level (Mean=3.69)	.452 (.059)	.000	.337	.568
Medium level (Mean=5.33)	.695 (.033)	.000	.631	.760
High level (Mean=6.00)	.794 (.040)	.000	.715	.873
Conditional effects of entertainment experience on consumers' technology readiness				
Low level (Mean=3.69)	.234 (.066)	.001	.103	.364
Medium level (Mean=5.33)	.089 (.056)	.115	-.022	.200
High level (Mean=6.00)	.030 (.071)	.671	-.110	.171

6. Discussion and Conclusion

6.1 Theoretical implications

As one of the first studies examining whether service robots' applications at different product/service levels in restaurants would influence customer experience, this study contributes to the applicability of the product level theory in both restaurant and theme park restaurant contexts. Although Kotler and Keller (2016) have suggested that this framework, originally designed for tangible products, should be extendable to intangible services and products, empirical validation in hospitality contexts in which the quality of intangible services defines the industry (Pizam, 2020), is still scarce (Ma et al., 2021). Building on a rigorous design with two studies guided by the framework, our study provided new and solid empirical evidence to the framework's application in hospitality and tourism contexts. Findings from both studies revealed consistent significant support of the three product levels on educational experience, but not entertainment experience. It demonstrates that in the contemporary era of technological applications, to customers at restaurants (Study 1) and tourists at theme park restaurants (Study 2), interacting with robots at restaurants create more educational experience than with human employees. Interestingly, in terms of creating entertainment experience, this study found no differences between robots and human employees.

Second, despite the growing interest among researchers in robots and AI technologies in hospitality and tourism (e.g., Lu et al., 2021; Murphy et al., 2017), existing studies have predominantly focused on how robots' features and performance could influence customers' experience (e.g., Lin & Mattila, 2021; Yu, 2020). There is a lack of critical inquiry on how different strategies of product designs incorporating robots may alter the experience. By embedding the product level theory framework into experimental design scenarios and placing robots at different levels of the dining product/service experience, our study provided a much more in-depth analysis of how such variations may influence customers. This approach also helps inspire future researchers aiming to engage in in-depth investigations on robotic applications in hospitality and tourism from the product and experience design perspective.

A third unique theoretical contribution of the study is that we position robotic restaurants as bearing the mission of showcasing the latest technologies to customers. This proposition aligns well with hospitality organizations' corporate social responsibilities on educational functions (e.g., Serra-Cantallops et al., 2018). Specifically, in the restaurant setting (Study 1), both educational and entertainment experiences exerted positive effects on technological readiness. On the other side, in the theme park restaurant setting (Study 2), educational experience significantly improved technological readiness while entertainment experience was not. The difference between the two settings in testing H3b maybe because tourists at theme parks spend more time on rides and sightseeing than on theme park restaurants. Additionally, rides at theme parks are normally designed with more advanced technological applications to create entertainment experience than at restaurants. Hence, to enhance theme park tourists' technology readiness via theme park restaurants, efforts should be on the design of the educational aspect. Building on the experience economy model (e.g., Pine & Gilmore, 1999), the findings of our study echo such a proposition and suggest that restaurants with robots could provide customers experiences, through which their technology readiness is further enhanced. Therefore, our study further contributes to technology readiness literature.

Fourth, to further contribute to knowledge on the formation of technology readiness, moderating effects of risk taking and social curiosity were tested. This study found that the higher extent of risk taking (Study 1) and social curiosity (Study 2), the stronger positive relationship between educational experience and technology readiness. These significant moderating effects offer important intellectual insights on how to take further steps on enhancing customers' technology readiness via educational experience at restaurants. Risk takers have the tendency to try risky experiences (Dawson et al., 2011; Kopalle et al., 2020), and therefore are willing to interact with and learn from restaurant robots, resulting in the improvement of their technology readiness. On the other side, customers with high social curiosity not only being curious about new technologies but also want to try new things that others are trying (Cheng & Guo, 2021; Cruz-Cárdenas et al., 2021; Kashdan et al., 2018), and therefore can enjoy educational experience created by robots as well as gaining technology readiness.

6.2 Practical implications

First, the study found that all three product/service layers, when overseen by robots instead of humans, could lead to enhanced educational experiences of customers, while no difference between human and robot performance was found in customers' entertainment experiences. The main takeaway here is that restaurant operators need to understand that while the costs of placing robots at different levels could vary significantly, the effects on customer experience are not likely to exhibit the same level of dynamic variation. Furthermore, the results of the three-way interaction effect indicated that in the situation of having human beings to offer core and facilitating products, using robots in the augmented function is more likely to develop consumers' educational experiences than using humans. Therefore, for the restaurants with limited financial resources, they could simply use robots to offer augmented products to increase the chance that consumers gain educational experience. In addition, for those restaurants who wish to emphasize entertaining experiences, using robots in single product level is less effective. In fact, they need to use robots for both augmented and facilitating products to develop consumers' entertaining experience. This finding has important implications on the operations and strategic decisions of restaurants currently using or considering using robots.

Second, hygiene and health concerns caused by COVID-19 have served as catalysts for robotic applications in hospitality. Still, the smooth introduction of robots in services is highly dependent on customers' technology readiness (Yang et al., 2021). As robotic restaurants and robotic applications in various service sectors are nascent, we believe hospitality organizations using robots also carry the mission and social responsibilities (intentionally or unintentionally) of showcasing the newest technologies to customers and the general public. Our findings are also encouraging insofar as through enhanced educational experience building through careful product design involving robots, customers' technology readiness is positively influenced. The findings yielded by this study provide valuable implications for restaurant managers considering incorporating purposefully designed educational experiences to shape customers' attitudes and intentions towards new technologies. This is also supported by the moderating effects of frequency of visit, given that customers with more experience with robotic restaurants also obtain more knowledge and better educational experience. As entertainment components serve the role to attract customers to visit robotic restaurants, we suggest that robotic restaurants add entertainment value (e.g., amusement, captivation, enjoyment, fun) to attract customers to patronize such establishments.

6.3 Limitations and future research

Our study is not free of limitations, which are acknowledged here. First, this study employed an experimental design method. Although it offers the advantage of testing cause-and-effect relationships, scenario-based experiments cannot take control of extraneous variables in natural environments. Therefore, any generalization of these findings should be attempted with caution. We suggest that future studies conduct on-site surveys at robotic restaurants or theme parks' robotic dining areas. Or, researchers may consider collaboration with firms to directly collect data via mobile apps of restaurants or theme parks, which have the potential to invite customers to rate their attitudes before, during, and after a dining experience. Second, as determined by its focus and relevance, the study only examined two dimensions of the experience economy model: educational and entertainment experiences. It has not assessed whether robotic applications would influence the escapism and aesthetic dimensions of customer experience, thus opening avenues for future research. Third, this study was conducted in China, and customers of different countries may have different feelings about, experiences with, and cultural norms regarding robotic restaurants. Therefore, we suggest that future studies be conducted in different countries as cross-cultural confirmation or to explore cultural differences.

Appendix 1: Scenario description in Studies 1 and 2

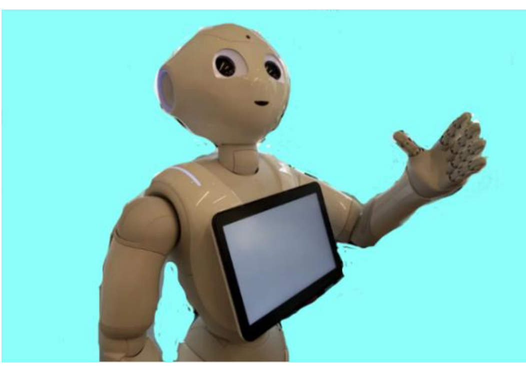
(In Study 1: Please imagine that you are dining in a local casual restaurant in China. In Study 2: Please imagine that you are visiting a theme park in a city in China, and having your lunch in this theme park). The average cost per person for this restaurant is RMB 100-200.

A service robot (see the picture below) greeted you, led you to your table, took your order, processed your payment, and later delivered the food to your table. (*A server greeted you, led you to your table, took your order, processed your payment, and later delivered the food to your table*).

While waiting for your food, you saw through the open kitchen, and found a number of robot cooks (see the picture below) were cooking food. Everything was fully automatic, from selecting ingredients to cooking. (*While waiting for your food, you saw through the open kitchen, and found a number of cooks were cooking food*).

While enjoying your food, you also saw a service robot (see the picture below) singing 'happy birthday song' to a group of customers near your table. (*While enjoying your food, you also saw a server singing 'happy birthday song' to a group of customers near your table*).

The below picture is shown in relevant Study 1 scenarios:



The below picture is shown in relevant Study 2 scenarios:

Appendix 2: Measure Items, Factor Loadings, and Reliability Scores

	Study 1		Study 2	
	Factor loading	Cronbach's alpha	Factor loading	Cronbach's alpha
Educational experience		.929		.869
The experience has made me more knowledgeable	.839		.858	
I learned a lot	.814		.839	
It stimulated my curiosity to learn new things	.835		.841	
It was a real learning experience	.827		.857	
Entertainment experience		.766		.739
Robots' services are amusing to watch / Servers' and chefs' services are amusing to watch / Servers' and chefs' services (including robots and humans) are amusing to watch.	.723		.767	
Watching robots perform services are captivating / Watching servers and chefs perform will be captivating / Watching servers and chefs (including robots and humans) perform will be captivating	.761		.758	
I really enjoy watching what service robots are doing / I really enjoy watching what servers and chefs are doing / I really enjoy watching what servers and chefs (including robots and humans) are doing	.816		.709	
Service deliveries of robots are fun to watch / Service deliveries of servers are fun to watch / Service deliveries of servers (including robots and humans) are fun to watch	.740		.772	
Technology readiness		.920		.909
Based on this dining experience, I believe that robots contribute to a better quality of life / I believe that new technologies contribute to a better quality of life	.828		.806	
Based on this dining experience, I believe that robots give me more freedom of mobility / I believe that technology gives me more freedom of mobility	.798		.805	
Based on this dining experience, I believe that robots give people more control over their daily lives / I believe that technology gives people more control over their daily lives	.744		.832	

Based on this dining experience, I believe that robots make me more productive in my personal life / I believe that technology makes me more productive in my personal life	.818		.814	
The dining experience makes me feel not difficult to understand robots / The dining experience makes me feel not difficult to understand high technology	.768		.753	
Based on this dining experience, I think that robots can be used by ordinary people / I think that high technology can be used by ordinary people	.768		.792	
Based on this dining experience, I would feel less discomfort when using robots / I would feel less discomfort when using high-tech product	.754		.842	
Risk taking		.792		NA
I am a risk taker	.912		NA	
I am adventurous	.912		NA	
Social curiosity		NA		.755
I like to learn about the habits of others.	NA		.876	
I like finding out why people behave the way they do.	NA		.852	
When other people are having a conversation, I like to find out what it’s about.	NA		.734	

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