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Consumer responses to the use of artificial intelligence in luxury and non-luxury restaurants

Chisato Nozawa[1,*], Taku Togawa[2], Carlos Velasco[3], & Kosuke Motoki[1,4,*]

[1] Department of Food Science and Business, Miyagi University, Sendai, Japan
[2] Faculty of Economics, Department of Management, Sophia University, Tokyo, Japan
[3] Centre for Multisensory Marketing, Department of Marketing, BI Norwegian Business School, Oslo, Norway
[4] Institute of Development, Aging and Cancer, Tohoku University, Sendai, Japan

*Equal contributions.
Correspondence should be addressed to: Kosuke Motoki, Department of Food Science and Business, Miyagi University, Sendai, Japan;
E-mail: motokik@myu.ac.jp

ABSTRACT

There has been an ever-increasing interest in artificial intelligence (AI) in the hospitality sector. However, it is still unclear how consumers respond to products/services in hospitality industries provided by AI. Building on the theoretical framework for using AI in different services and the literature on luxury consumption across four studies, we investigated how consumers evaluate different types of restaurants that are run by AI vs. humans. The results demonstrated that consumers evaluated food and restaurants more negatively where AI work (Study 1). This effect was higher in luxury restaurants compared to casual dining (fast food, casual restaurants) (Studies 2 and 3). Moreover, we identified the underlying mechanism of this effect by showing that in luxury (vs. casual) restaurants, foods cooked by AI negatively influenced evaluations of three dimensions of restaurants' quality, such as food, service, and ambience quality, decreasing the intention to visit the restaurant (Study 4). Altogether, these findings reveal some impacts that AI can have in the hospitality industry and provide practical insights on how to introduce AI in restaurants.

Keywords: Artificial intelligence; Luxury consumption; Foods; Human-computer interaction; Restaurants

1. Introduction

Over the last decade, there has been an increasing interest in new technologies such as artificial intelligence (AI) among consumers, industries, and society (e.g., Evanschitzky et al., 2020; Klaus & Zaichkowsky, 2020). The interests in AI in hospitality have also been growingly increasing. This can be traced back to Collier (1983), who argued that the automation revolution would come in hospitality industries, including restaurants (Collier, 1983). AI can be defined as '*computational agents that act intelligently*' (Poole & Mackworth, 2010 p.3), though there might be no consensus of its definition (see De Bruyn et al., 2020). Currently, AI have been applied to a range of aspects in the hospitality industry, including front desk clerks (i.e., check-in and check-out), greeting, cooking, cleaning, escorting, and delivery service (e.g., Robinson et al., 2020; Stanislav & Craig, 2019; Wirtz et al., 2018). Although several studies recently investigated the role of AI in the hospitality sector (e.g., Shin & Jeong, 2020; Tussyadiah & Park, 2018), most of the research has focussed on AI in the context of tourism (e.g., Shin & Jeong, 2020; Tussyadiah & Park, 2018). Consumer behaviours in the context of restaurants are yet to be adequately examined in the literature (see Table 1, for a summary of the studies on the topic).

Applications of AI in the restaurant industry are promising (Berezina et al., 2019). AI might be useful in reducing errors, portion control, and cost control in the restaurant industry (Berezina et al., 2019). Indeed, a report forecasts that AI will have a significant impact on the restaurant industry by 2025 (Oracle, 2019). The role of AI and robots will be expanding in the restaurant industry, including kitchen preparation, quality checking in the kitchen, staff training, serving guests, seating guests, etc (Oracle, 2019). Robotic chefs are an emerging reality in the restaurant industry (Berezina et al., 2019; Seyitoğlu & Ivanov, 2020a). Some innovative restaurants, such as Spyce, Jingdong X Future, and Moley, have already featured a robotic kitchen, chefs, and/or waiters. One example of this is a robot bartender in Tokyo named *Yoronotaki* (Kelly & Tomoshige, 2020) who serves up drinks in a pub and mixes a cocktail in a minute. Moreover, a recent survey demonstrated that the importance of this service has been increasing during the period of COVID-19 (Bucak & Yiğit, 2021). It has been also predicted that the use of AI (e.g., robots) in kitchens will increase after the COVID-19 outbreak (Bucak & Yiğit, 2021). Based on these needs of both industry and society, this study investigates how consumers perceive food prepared by AI in the context of restaurants.

Table 1. Summary of studies on consumer responses to the use of AI and/or robots.

Study	Products/services	Independent variable(s)	Dependent variable(s)	Key findings
Ivanov et al., (2018)	- Hotel services	- Gender, education, etc.	- Attitudes towards the use of robots in hotels	- Men regard robots as more acceptable than women
Tussyadiah & Park (2018)	- Hotel services	- Different hotel service robots (NAO and Relay)	- Anthropomorphism, animacy, likeability, perceived intelligence and perceived security	- Intention to adopt hotel service robots influenced by anthropomorphism, perceived intelligence and perceived security. - NAO's adoption related to anthropomorphism and perceived security - Relay's adoption linked with perceived intelligence
Chan & Tung (2019)	- Hotel services	- Service provider (human, robot), hotel types (budget, midscale and luxury)	- Hotel brand experiences (sensory, affective, behavioural and intellectual)	- Robotic (vs. human) service is rated as higher sensory and intellectual experience across all hotel segments.

				- Robotic (vs. human) service is rated as higher behavioural experience at midscale and budget hotels. - Robotic (vs. human) service is rated as lower affective experience across all hotel segments.
Longoni et al., (2019)	- Medical services	- Service provider (AI, humans)	- Likelihood to utilise, willingness-to-pay, and preferences.	- Consumers are more reluctant to utilise healthcare delivered by AI (vs. human) providers
Ho et al., (2020)	- Hotel services	- Different sources of service recovery (human staff, service robot and fellow customer)	- Service experience following a service failure	- Service evaluation is less favoured following fellow customer's help (vs. the others). - Service evaluation is not different between help from human staff and service robot.

Longoni, & Cian (2020).	- Products (e.g., hair treatment sample, chocolate varieties)	- Recommenders (AI, humans), goals (hedonic, utilitarian)	- Product choice	- Preferences for AI (vs. human) recommenders are increased when the goal is utilitarian
Mende et al., (2020)	- Food, educational and medical services	- Service provider (Humanoid robots, humans)	- Compensatory behaviors (e.g., increased caloric intake)	- Participants tended to engage in compensatory behaviours (e.g., ate more unhealthy foods) with humanoid robots (vs. human)
Shin & Jeong (2020)	- Hotel services	- Morphology (anthropomorphic, zoomorphic, caricatured), Interactivity (high, low), Hotel types (luxury, mid-scale and economy/budget)	- Attitudes, intention	- Positive attitudes towards caricatured robots than other robots - No significant results in the interactivity and hotel types
Zhu & Chang (2020)	- Food services	- Robotic chef anthropomorphism	- Food quality prediction, warmth and competence	- Warmth and competence mediate the relationship between robotic chef anthropomorphis

				m and food quality prediction
Borau et al., (2021)	- Chat bots	- Gender of robots (male, female)	- Attitudes toward the robots	- Female bots are preferred over male bots though perceived warmth
Kim et al., (2021)	- Hotel services	- Risk salience of COVID-19 (yes, no) - Hotel staff (Robot-staffed hotel, human-staffed hotel)	- Choice of a hotel from two options (i.e., a robot-staffed vs. a human-staffed hotel)	- Preferences for the robot-staffed (vs. human-staffed) hotel is higher in the condition of risk salience of COVID-19.
Longoni et al., (2021)	- News media	- Tagging news written by different sources (AI, human reporter)	- Perceived accuracy	- News items produced by AI (vs. human) are more likely to be rated as inaccurate
Lu et al., (2021)	- Food services	- Human-likeness of attributes (visual, vocal and verbal)	- Service encounter evaluation, revisit intentions and positive word of mouth intentions	- Humanlike voice is a dominant attribute affecting all three evaluations
McLean et al., (2021)	- AI voice assistants	- Social presence, perceived intelligence, perceived	- Consumer brand engagement	- Social presence, perceived intelligence, perceived ease of use and other

		ease of use and so on.		variables influencing consumer brand engagement
Zhang et al., (2021)	- Financial services	- Financial advisors (human, robots)	- Perceptions of trust, performance expectancy and intention to hire	- Evaluation of human financial advisors with high expertise are higher than robot advisors
The present research	- Food services	- Cooking staff (AI, humans) - Status (Luxury, non-luxury)	- Consumer preferences (intention to eat, intention to visit)	- Consumers evaluate food and restaurants more negatively where AI (vs. humans) work, and this effect is higher in luxury (vs. non-luxury) restaurants.

2. Theoretical background

2.1. The theoretical framework for using AI in different services

This study relies on the theoretical framework for using AI in different tasks and services (Huang & Rust, 2021; Wirtz et al., 2018), as opposed to humans or in collaboration with humans. According to Huang and Rust (2021), there are three categories of tasks and services where AI can provide different benefits. The categories include mechanical tasks in transaction services (e.g., fast-food ordering and delivery), thinking tasks in utilitarian services (e.g., product recommendation system), and feeling tasks in hedonic services (e.g., sophisticated chatbot). Specifically, the framework suggests that (1) mechanical services should be performed by AI, (2) thinking service by both AI and humans, and (3) feeling services by humans. Similarly, a conceptual framework on service robots also suggests that they (possibly including AI) are better suited for cognitive and analytically demanding tasks rather than for complex emotional/social tasks (Wirtz et al., 2018). At present, humans are more suited for complex emotional/social tasks; however, in contexts where there are both emotional/social tasks and high cognitive-analytical demands, the collaboration of humans and service robots will be more fruitful. One research has also shown that people are less likely to associate robots with emotion-oriented jobs (e.g., therapist) than cognition-oriented ones (e.g., computer programmer) (Waytz & Norton, 2014). These theoretical frameworks suggest that consumers might perceive the AI provider as having less (emotional) experiences, and accordingly, tend to devalue the emotion-oriented products/services provided by AI.

2.2. The role of AI in hedonic and utilitarian consumption

Previous research suggests that AI is more associated with utilitarian rather than hedonic consumption (Longoni & Cian, 2020). Although consumers respond more negatively to products/services provided by AI than by humans in general (e.g., Ivanov et al., 2020; Longoni et al., 2019; Mende et al., 2019), the effects differ in hedonic and utilitarian consumption (Longoni & Cian, 2020). Hedonic consumption involves experiential, emotional, and sensory dimensions of value, while utilitarian consumption denotes factual, rational, and logical dimensions of value (Motoki et al., 2019; Voss et al., 2003). In other words, hedonic consumption is emotionally driven, while utilitarian consumption is cognitively driven. According to Longoni and Cian (2020), consumers have lay beliefs associating AI with being less hedonic and more utilitarian. Lay beliefs have been constructed by the learning process (e.g., personal experiences and environments) throughout development (Morris et al., 2001; Ross & Nisbett, 2011). An example of the expression of lay beliefs is the idiom of ‘thinking like a robot’. Actually, it has been demonstrated that consumers prefer product/service recommendations by humans when the hedonic goal is activated (i.e., when consumers care about hedonic characteristics of products/services) (Longoni & Cian, 2020). However, they prefer product/service recommendations by AI when utilitarian goals are activated (i.e., when consumers care about utilitarian characteristics of products/services) (Longoni & Cian, 2020). Together, these findings suggest that hospitality services involving AI might be less suitable for hedonic than utilitarian consumption.

2.3. Affective experiences in luxury restaurants

The last two decades have seen a rapid growth in luxury segments of the restaurant industry (Hwang & Hyun, 2013; Hyun & Kang, 2014; Velasco & Veflen, 2021). People have specific impressions of luxury restaurants, including expensive prices, high quality of food, service, and ambience as well as emotions (pleasure, elegance) (Lee & Hwang, 2011). A luxury restaurant is a full-service restaurant whose atmospherics (e.g., décor, physical environment, services) and products (e.g., food, beverage) are carefully prepared and superior in quality (Peng and Chen, 2015). Substantial evidence has shown that luxury consumption is associated with hedonic pleasure (Hagtvedt & Patrick, 2009). For example, luxury experiences have been conceptualized as a hedonic escape (Holmqvist et al., 2020). In the field of luxury restaurants, hedonic feelings have been considered as an important aspect of its value (Lee & Hwang, 2011). A desire for hedonism (e.g., a luxury restaurant is truly a joy) influences consumers' positive attitudes towards luxury restaurants (Lee & Hwang, 2011). Furthermore, among the four dimensions of luxury restaurant value (functional, hedonic, symbolic/expressive, and financial value), hedonic value primarily influences consumer's purchase intention (Yang et al., 2016). Together, these findings suggest that luxury restaurants involve more hedonic value than non-luxury restaurants.

2.4. Remaining questions and hypothesis on the role of AI in consumer preferences for luxury and non-luxury restaurants

To our understanding, no research has investigated the role of AI in consumer preferences for luxury and non-luxury restaurants. Most research in the hospitality sector has treated AI in the context of hotel industries or tourism (e.g., Ho et al., 2020; Tussyadiah & Park, 2018). A few studies have investigated how consumers evaluate food services provided by AI (e.g., Fusté-Forné, 2021; Lu et al., 2021). However, to our knowledge, the interactive effects of restaurant types (luxury, non-luxury) and service providers (AI, humans) on consumer's preferences have not been examined. Based on the theory of mind perception and affective experiences in luxury restaurants, this study investigated how consumers evaluate luxury and non-luxury restaurants with services provided by AI versus humans.

Previous studies have shown that consumers tend to prefer products/services provided by AI to humans (e.g., Ivanov et al., 2020; Longoni et al., 2019; Mende et al., 2019). Hence, it is expected that consumers' preference for restaurants involving AI will be lower than those involving humans. Past research also suggests that luxury restaurants are more predominant in hedonic value than non-luxury restaurants (e.g., Lee & Hwang, 2011). Consumers tend to devalue the hedonic products/services provided by AI (Granulo et al., 2020; Longoni & Cian, 2020). Hence, we establish the following hypothesis:

H1: Consumers will indicate a lower preference for the restaurant that uses AI versus humans for operations, such as food preparation.

H2: The effect expected will be more prominent in the context of luxury restaurants rather than that of non-luxury restaurants.

2.5. Food, service, and atmosphere quality as mediators

Several quality attributes influencing preferences for restaurants (e.g., intention to visit) have been identified (e.g., Gupta et al., 2007; Ha & Jang, 2010; Han & Hyun, 2017). For example, Kim et al. (2009) identified six attributes of a restaurant's quality—food quality, service quality, atmosphere, convenience, price, and value. Among these quality attributes, the quality of food, service, and physical environment (atmosphere) are commonly mentioned as restaurant-quality attributes (e.g., Bujisic et al., 2014; Hwang & Ok, 2013; Lee & Hwang, 2011). Specifically, three common attributes (food, service, and ambience) have been proposed in luxury and non-luxury restaurants (Bujisic et al., 2014). Given that this research treats both luxury and non-luxury restaurants, we followed this classification (Bujisic et al., 2014) and further discussed these three attributes of a restaurant's quality.

Expectations of food, service, and ambience quality influence preferences for restaurants. Food quality consists of various food-related attributes, such as tastiness, freshness, visual attractiveness, and variety of food options on the menu (e.g., Han & Hyun, 2017; Hwang & Ok, 2013; Motoki et al., 2018). Service quality includes the interaction process between customers and employees, such as service employees' responsiveness, assurance, and empathy (e.g., Brady & Robertson, 2001; Hwang & Ok, 2013; Jang & Namkung, 2009). Ambience quality consists of store attributes, such as interior design, lighting, background music, spatial layout, dining area layout, temperature, and semantic feelings caused by the environments (e.g., stylish, fancy) (Hwang & Hyun, 2013; Hwang & Ok, 2013; Jang & Namkung, 2009). Previous studies have reported that food, service, and ambience quality are positively associated with the evaluation of, and behavioural intention associated with, restaurants (Bujisic et al., 2014; Han & Hyun, 2017). Hence, it seems possible that consumers' perception of a restaurant's quality will mediate the effects of AI on the intention to visit the restaurants.

2.6. Halo (horn) effect as the underlying mechanisms of mediating roles of food, service, and atmosphere quality

We expected that regarding luxury restaurants, consumers evaluated the restaurants negatively that employed AI kitchen staff. To identify the underlying mechanisms of this effect, we focused on the role of consumers' expectations for the restaurant's quality as a mediator in the moderated mediation model. That is, in the context of luxury restaurants, the use of AI for food preparation will lead to negative expectations for the quality of its foods, service, and ambience, resulting in lower intention to visit the restaurant. It might be unintuitive that the foods cooked by AI lead to negative expectations not only for the foods but also for the restaurant's service and ambience. However, based on the theory of halo effect, it is plausible that negative evaluation of the food cooked by AI kitchen staff will spill over to consumers' expectations for the other dimensions of the restaurant's quality, such as service and ambience.

The term 'halo (horn) effect' refers to a positive (negative) judgement bias in which an attribute of products/services determines the impression of other conceptually distinct attributes (Burton et al., 2015; Richetin et al., 2019). For example, a food product with a fair-trade label tends to be perceived as a lower calorie even though calorie is unrelated to a fair-trade (Schuldt et al., 2012). Other examples show that organic labels positively influence sensory and hedonic evaluations (Apaolaza et al., 2017). In a restaurant setting, a restaurant using locally sourced food tends to be perceived as environmentally friendly, serving a healthy menu, and conveniently located (Bacig & Young, 2019). Hence, we built the third hypothesis as follows:

H3: Consumers' expectations for the restaurants' quality will mediate the effects of types of service providers and restaurant type on consumers' intention to visit the restaurant. Specifically, in the context of luxury restaurants, using AI (vs. human) kitchen staff will more likely decrease consumers' expectations for the quality of the restaurant's (a) food, (b) service, and (c) ambience compared to that of non-luxury restaurants, in turn decreasing the intention to visit the restaurant.

2.7. Overview of the present research

Across four studies, this research aimed to investigate the role of AI in consumer preferences for the two types of restaurants (luxury and non-luxury) and uncover some of the mechanisms that may explain such preferences (Table 2). Prior to the discussion about the restaurant context and establishing a reference point, Study 1 investigated consumers' general attitudes towards luxury and non-luxury goods provided by AI and humans, which included several categories of products/services, such as restaurants, clothing, and medical services. Studies 2 and 3 tested consumers' preferences for food provided by AI in luxury and non-luxury restaurants. Therefore, the studies measured participants' intention to eat as a dependent variable associated with consumers' preferences for restaurant settings. Study 4 investigated the mediating role of restaurant quality (food, service, and ambience quality) in the effects of AI cooking staff on consumers' preferences for luxury and non-luxury restaurants. Thus, Study 4 measured behavioural intention to restaurants (i.e., visit intention) as a main dependent variable.

Table 2. Summary of the four studies conducted.

	Study 1	Study 2	Study 3	Study 4
Purpose	- To examine how consumers associate AI and humans with luxury images.	- To examine how cooking staff (AI vs. humans) influence consumers' preferences for luxury and non-	- To examine how cooking staff (AI vs. humans) influence consumer preferences for luxury and non-	- To examine the mediating role of restaurant qualities (food, service and ambience quality) in the effects of AI (vs. humans)

		luxury restaurants.	luxury restaurants	cooking staff on consumer preferences for luxury and non-luxury restaurants.
Design	- 2 (service provider: AI, human) × 2 (product type: luxury, non-luxury) - All factors being within-participants	- 2 (service provider: AI, human) × 2 (restaurant type: luxury, non-luxury) - All factors being within-participants	- 2 (service staff: AI, human) × 2 (restaurant type: luxury, non-luxury) - The service staff as a within-participant, the restaurant type as a between-participant	- 2 (service staff: AI, human) × 2 (restaurant type: luxury, non-luxury) - All factors being between-participants
Main dependant variable	- The desirability of products/services	- The intention to eat the food	- The intention to eat the food	- The intention to visit restaurants
Final number of participants	- 101 Japanese participants (31 females, 65 males, 5 unanswered, mean age of	- 103 Japanese participants (36 females, 63 males, 4	- Study 3A: 203 Japanese participants (83 females,	- 386 Japanese participants (155 females, 223 males,

	43.25 years, SD = 9.20)	unanswered, mean age of 41.30 years, SD = 9.99)	119 males, 1 unanswered, mean age of 41.93 years, SD = 9.49) - Study 3B: 200 UK participants (147 females, 52 males, 1 unanswered, mean age of 34.81 years, SD = 11.43)	8 unanswered, mean age of 42.25 years, SD = 10.55)

3. Study 1

Study 1 aimed to examine how consumers associate AI and humans with luxury images.

3.1. Design and participants

The study followed a 2 (service provider: AI, human) × 2 (product type: luxury, non-luxury) experimental design, in which all factors were within-participant. The main dependent variable was the desirability of products/services. We also measured scarcity, compassion, effort, and quality for the price as additional dependent variables.

In total, 101 Japanese participants (31 females, 65 males, 5 unanswered, mean age of 43.25 years, SD = 9.20) were recruited on Lancers (https://www.lancers.jp/) and completed a survey on Qualtrics (https://www.qualtrics.com/jp/). We recruited Japanese participants for all the studies. Considering Japan's technology adoption, there is a promising future when it comes to adopting AI chefs. As a matter of fact, an innovative food service company has already introduced this new technology (e.g., robotic bar in Tokyo; see Kelly & Tomoshige, 2020). All the studies described herein were approved by the ethics committee of Miyagi University and were conducted in accordance with the Declaration of Helsinki.

Participants were required to answer questions about impression towards products/services made by humans or AI. First, participants were asked about 'We are considering creating products and services made by AI [humans]. Examples are restaurant menu, clothing, and medical services. Please answer "how desirable are luxury [cheap] products and services made by artificial intelligence [humans]?". The responses were recorded on a 7-point Likert-scale (1: not at all, 7: very much). The order of conditions (AI and luxury, AI and non-luxury, human and luxury, human and non-luxury) was randomized within participants. The procedure and results of additional dependent variables (scarcity, love, effort, and quality for the price) are shown in Appendix of Supplementary Material.

3.2. Statistical Analysis

A repeated measures ANOVA was applied to assess the effects of the service provider and status on the desirability of products and service. The analysis followed a 2 (service provider: AI, humans) × 2 (status: luxury, non-luxury) within-participant design. The dependent variable was ratings of the desirability of products/services. If an interaction term was observed, post-hoc analysis was conducted to elucidate the details of the interaction. This analysis was conducted using multiple testing by Holm's procedure. Additional ANOVAs were also conducted to assess the effects of the service provider and status on the impression of the products/services. The dependent variables were scarcity, compassion, effort, and quality for the price. All the ANOVAs and subsequent multiple testing were carried out using HAD software (Shimizu, 2016).

3.3. Results of the desirability of products and services

The analysis revealed main effects of service providers ($F_{1,100}$ = 46.31, p < .001 η^2_p = 0.317) and luxury status ($F_{1,100}$ = 5.37, p = .022, η^2_p = 0.051). The analysis showed a significant interaction between service provider and luxury status ($F_{1,100}$ = 56.17, p < .001, η^2_p = 0.36; Figure 1). Post hoc comparisons revealed that human (vs. AI) staff increased the desirability of luxury products/services (M_{human} = 5.35 ± 1.41, M_{AI} = 3.41 ± 1.39, $t_{1,100}$ = 11.36, p < .001, d = 1.84). However, no significant differences were observed for the desirability of cheap products/services (M_{AI} = 4.86 ± 1.55, M_{human} = 4.56 ± 1.40, $t_{1,100}$ = 1.74, p = .085, d = 0.21). These results support our predictions: desirability is lower for products and services provided by AI than humans (H1), which is more prominent in the context of luxury (H2).

4. Study 2

Study 2 aimed to examine the effects of service provider (AI vs. humas) influences consumers' preferences for luxury and non-luxury restaurants.

4.1. Design and participants

The study followed a 2 (service provider: AI, human) × 2 (restaurant type: luxury, non-luxury) experimental design, in which all factors were within-participant. The main dependent variable was intention to eat the foods. Data were collected from 103 Japanese participants (36 females, 63 males, 4 unanswered, mean age of 41.30 years, SD = 9.99) who completed a survey on Google Forms.

Participants responded to the question about the influence of cooking staff (AI vs. humans) on the intention to eat food at luxury or non-luxury (fast food) restaurants. They were asked to answer: 'How much would you like to eat food at luxury restaurants [fast food] made by artificial intelligence [humans]'. All responses were recorded on Likert-scales ranging from 1 (not at all) to 7 (very much). The order of conditions (AI and luxury, AI and non-luxury, human and luxury, human and non-luxury) was randomized within participants.

4.2. Statistical Analysis

A repeated measures ANOVA was applied to assess the effects of the service provider and restaurant type on the intention to eat the food. The analysis followed a 2 (service provider: AI, humans) × 2 (restaurant type: luxury, non-luxury) within-participant design. The dependent variable was ratings of the intention to eat the food. Post-hoc analysis was conducted as in Study 1.

4.3. Results

The analysis revealed main effects of service staff ($F_{1,103}$= 16.81, p < .001 η^2_p= 0.140) and restaurant type ($F_{1,103}$= 80.86, p < .001, η^2_p= 0.44). The analysis showed a significant interaction between service staff and restaurant type ($F_{1,103}$= 51.48, p < .001, η^2_p= 0.333; Figure 1). Post hoc comparisons revealed that human staff increased the intention to eat at both luxury (M_{AI}= 4.29 ± 1.42, M_{human}= 5.86 ± 1.15, $t_{1,103}$ = 9.92, p < .001, d= 1.36) and fast-food restaurants (M_{AI}= 4.36 ± 1.34, M_{human}= 4.80 ± 1.29, $t_{1,103}$ = 2.80, p = .006, d= 0.29). Although the findings were slightly different from those in Study 1, the effect size of service provider was larger (vs. AI) at luxury restaurants than at fast food restaurants. Thus, in addition to Study 1, we found additional support of both H1 and H2 in the study.

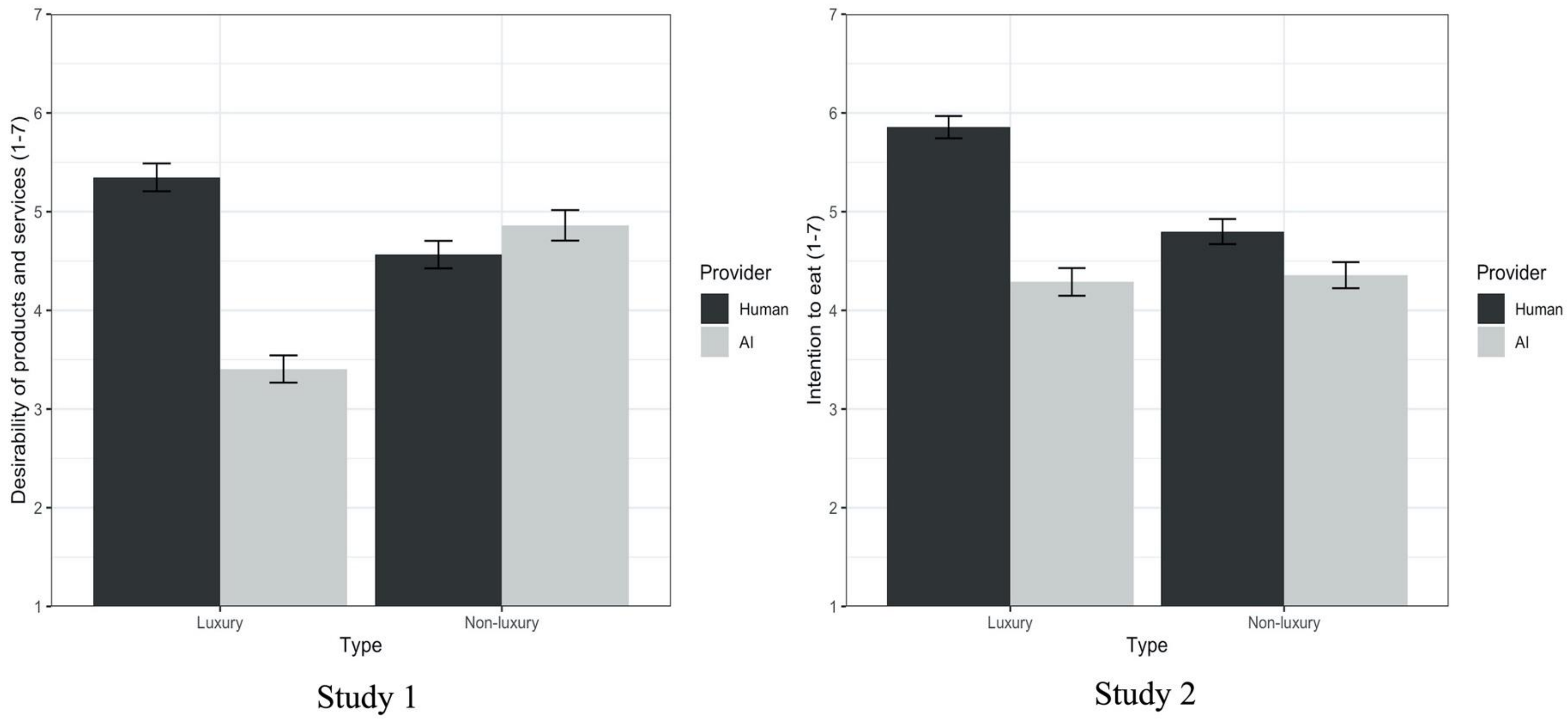


Figure 1. Influences of the service provider and the luxury type on the desirability of products/services (Study 1) and the intention to eat the food (Study 2). The Likert rating scale ranged from 1–7 ('not at all' to 'very much'). Error bars represent standard errors of the mean.

5. Study 3

Study 3 aimed to examine how service provider (AI vs. humans) influence consumer preferences for luxury and non-luxury restaurants by using mixed design with service provider (cooking staff) as a between-participants factor. Study 2 employed within-participants design in which participants experienced all conditions. However, since the within-participants design might cause demand characteristics (Charness et al., 2012) and relative compatibility effects, different experimental designs (within or between) sometimes yield different results (e.g., Charness et al., 2012; Motoki & Velasco, 2021). Therefore, Study 3 followed a main experimental manipulation (service provider) as a between factor. Whereas all the previous experiments were conducted in Japan, Study 3 investigated whether our previous findings can be generalized into the other country.

5.1. Design and participants

The study followed a 2 (service staff: AI, human) × 2 (restaurant type: luxury, non-luxury). As with the previous experiments, the service staff was a within-participants factor, whereas in this case, the restaurant type was manipulated as a between-participants factor. Data of Study 3A were collected from 203 Japanese participants (83 females, 119 males, 1 unanswered, mean age of 41.93 years, SD = 9.49). Data of Study 3B were collected from 200 UK participants (147 females, 52 males, 1 unanswered, mean age of 34.81 years, SD = 11.43). We used the same questions as those used in Study 2. The procedure of Study 3B was pre-registered (https://aspredicted.org/2G4_PD2).

5.2. Statistical Analysis

The analysis followed a 2 (service provider: AI, humans) × 2 (restaurant type: luxury, non-luxury) mixed design ANOVA with service provider as between-participant factor and restaurant type as within-participant factor. The dependent variable was ratings of the intention to eat the food. Post-hoc analysis was conducted as in the same as in Studies 1 and 2.

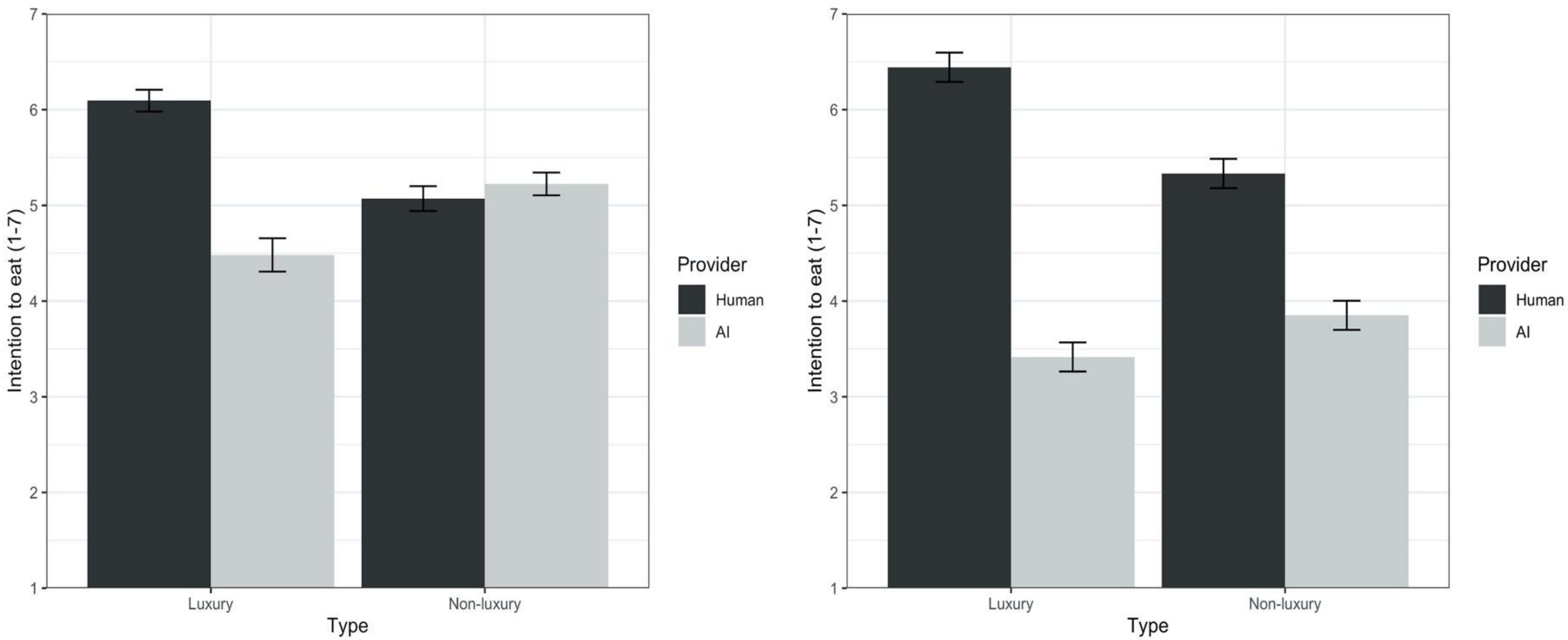
5.3. Results of Japanese participants (Study 3A)

The analysis revealed a main effect of service staff ($F_{1,198}$ = 31.89, p < .001 η^2_p = 0.139) but not of restaurant type ($F_{1,198}$ = 1.158, p = .283, η^2_p = 0.006). The analysis showed a significant interaction between service staff and restaurant type ($F_{1,198}$ = 92.35, p < .001,

η^2_p = 0.318; Figure 2). Post hoc comparisons revealed that AI (vs. human) staff decreased participants' intention to eat the food at luxury restaurants (M_{AI} = 4.26 ± 1.64., M_{human} = 6.09 ± 1.05, $t_{1,396}$ = -9.757, p < .001, d = -2.638). However, no significant differences were observed for the intention to eat the food at fast food restaurants (M_{AI} = 5.08 ± 1.18, M_{human} = 5.07 ± 1.20, $t_{1,396}$ = -0.041, p = .967, d = 0.008). Therefore, in addition to the previous studies conducted with within-participants design, H1 and H2 were replicated again in Study 3, which employed between-participants design for manipulation of the service staff. It should be noted that the effect sizes of post hoc comparisons appear similar in Studies 1 and 2.

5.4. Results of UK participants (Study 3B)

The analysis revealed main effects of service staff ($F_{1,198}$ = 145.34, p < .001 η^2_p = 0.423) and of restaurant type ($F_{1,198}$ = 9.37, p = .003, η^2_p = 0.045). The analysis showed a significant interaction between service staff and restaurant type ($F_{1,198}$ = 49.97, p < .001, η^2_p = 0.201; Figure 2). Post hoc comparisons revealed that AI (vs. human) staff decreased participants' intention to eat the food at luxury restaurants (M_{AI} = 3.42 ± 1.84, M_{human} = 6.43 ± 0.97, $t_{1,396}$ = -13.98, p < .001, d = -3.736) and at fast-food restaurants (M_{AI} = 3.85 ± 1.76, M_{human} = 5.33 ± 1.37, $t_{1,396}$ = -6.86, p < .001, d = -1.370). The effect sizes indicate that difference between AI and humans was smaller at at fast-food (d = -1.370) compared to luxury restaurants (d = -3.736). In other words, participants were less reluctant to eat the food cooked by AI (vs. humans) at fast-food compared to luxury restaurants. Post hoc comparisons also showed that food preferences cooked by humans were greater at luxury (vs. fast-food) restaurants ($t_{1,396}$ = 7.127, p < .001, d = 0.961), while food preferences cooked by AI were greater at fast-food (vs. luxury) restaurants ($t_{1,396}$ = 2.848, p = .005, d = 0.284).



Study 3A
(Japanese participants)

Study 3B
(UK participants)

Figure 2. Influences of the service provider (AI, humans) and restaurant type (luxury, fast food) on the intention to eat the foods. The Likert rating scale ranged from 1–7 (‘not at all’ to ‘very much’). Error bars represent standard errors of the mean.

6. Study 4

Study 4 aimed to examine the mediating role of restaurant qualities (food, service, and ambience quality) in the effects of AI (vs. humans) service provider on consumer preferences for luxury and non-luxury restaurants.

6.1. Design and participants

The study was a 2 (service staff: AI, human) × 2 (restaurant type: luxury, non-luxury) in which all factors being between-participants. Participants were randomly assigned to one of the four conditions. In total, 400 participants were recruited. Fourteen participants who failed the attention check question were excluded from the analyses. The final data was n = 386 (155 females, 223 males, 8 unanswered, mean age of 42.25 years, SD = 10.55). We preregistered the data collection and analysis plan for this study at https://osf.io/qk6n8/.

6.2. Materials and procedure

Participants were told that 'There is a luxury [casual] restaurant using automatic cooking by AI [human-made cooking]'. Subsequently, they were asked 'How much would you like to visit this restaurant?' The responses were recorded on a 7-point Likert-scale (1: not at all, 7: very much). Then, they were asked about their expectations regarding the restaurant. They answered 12 items using a 7-point Likert-scale. The expectation included dimensions of three restaurant qualities: food (tastiness, freshness, visual appeal, variety of food menu), service (employees' friendliness, responsiveness to check and order, trustworthiness, and competence), and ambience quality (appeal of interior design, stylish ambience, comfortable ambience, fancy and elegant ambience). Each of the items were created based on previous research on restaurant qualities (e.g., Kim et al., 2009; Ha & Jang, 2010). The details of the questions are shown in Appendix of Supplementary Material. The order of 12 items was randomized. These ratings were averaged into a measure of each dimension of restaurant qualities: food (α = .772), service (α = .826), and ambience quality (α = .828).

Finally, they answered the two questions for attention check and provided their demographic information (gender, age).

6.3. Statistical Analysis

A two-way ANOVA was applied to assess the effects of the service provider and restaurant type on the intention to visit the restaurant. The analysis followed a 2 (service provider: AI, humans) × 2 (restaurant type: luxury, non-luxury) between-participant design. The dependent variable was ratings of the visit intention to restaurants. In past research, visit intention has often been used as a measure of behavioural intention to restaurants (Fakih et al., 2016). Post-hoc analysis was conducted same as in Studies 1–3. Additional ANOVAs were also conducted to assess the effects of the service provider and restaurant type on three food qualities. The dependent variables were food, service, and ambience quality.

To investigate whether the restaurant's quality rating mediated the effect of service staff and restaurant type on the visit intention, we ran a moderated mediation analysis (PROCESS Model 7; Hayes 2017) with the service provider (dummy coding: 0 = human and 1 = AI) as the independent variable, visit intention as the dependent variable, restaurant's quality [the quality of food, service, or ambience] as the mediator, and restaurant type (dummy coding: 0 =non-luxury restaurants and 1 = luxury restaurants) as the moderator.

6.4. Results

The analysis of the visit intention revealed a main effect of the service staff but not of the restaurant type. The analysis of the restaurant qualities revealed main effects of service staff and restaurant type on the perceived quality of food, service, and ambience. The analysis showed a significant interaction between the service staff and restaurant type on visit intention and these perceived qualities. Post hoc comparisons revealed that human staff increased visit intention and food and service qualities at both luxury restaurants and non-luxury restaurants. Post hoc comparisons also revealed that human staff increased the ambience quality at luxury restaurants. However, no significant differences were observed for ambience quality at non-luxury restaurants. The results are shown in Figure 3 and Tables 3. Descriptive statistics of the results in Study 4 are shown in Appendix of Supplementary Material.

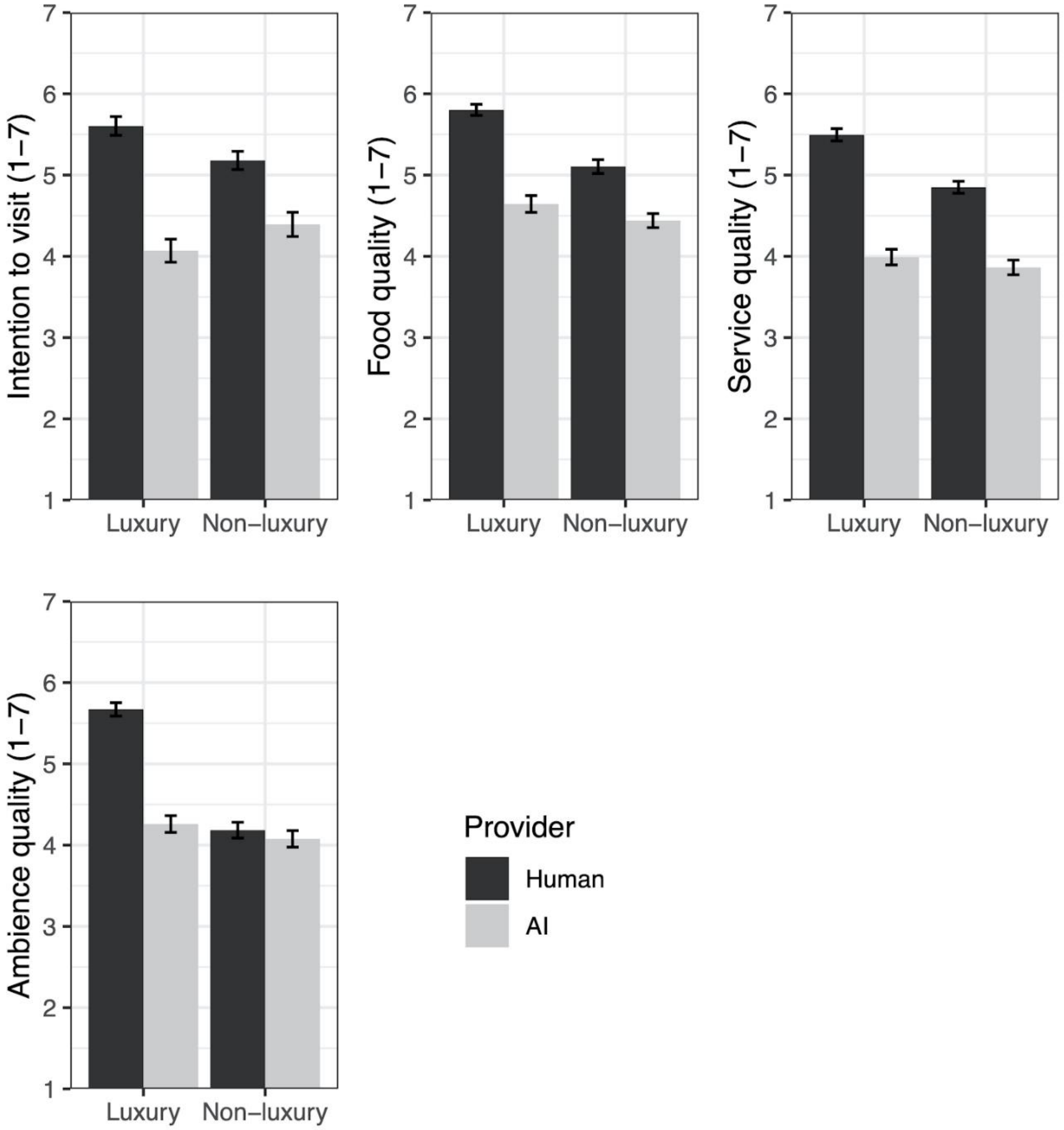


Figure 3. Influences of the service provider (AI, humans) and restaurant type (luxury, non-luxury) on the visit intention and perceived restaurant quality (food, service, and ambience quality). The Likert rating scale ranged from 1–7 (‘not at all’ to ‘very much’). Error bars represent standard errors of the mean.

Table 3. Results of ANOVA in Study 4.

	Visit intention	Food quality	Service quality	Ambience quality
Effect				
Provider	**F = 79.96, p < .001, η^2_p = 0.173**	**F = 108.88, p < .001, η^2_p = 0.222**	**F = 216.01, p < .001, η^2_p = 0.361**	**F = 61.41, p < .001, η^2_p = 0.138**
Restaurant type	**F = 0.15, p = .699, η^2_p = 0.000**	**F = 26.54, p < .001, η^2_p = 0.065**	**F = 20.74, p < .001, η^2_p = 0.051**	**F = 74.12, p < .001, η^2_p = 0.163**
Provider × restaurant type	**F = 8.29, p = .004, η^2_p = 0.021**	**F = 7.99, p = .005, η^2_p = 0.020**	**F = 9.34, p = .002, η^2_p = 0.024**	**F = 45.23, p < .001, η^2_p = 0.106**
Post hoc comparisons				
Human vs. AI at luxury restaurants	**t = 8.58, p < .001, d = 1.140**	**t = 9.62, p < .001, d = 1.810**	**t = 12.88, p < .001, d = 2.423**	**t = 10.57, p < .001, d = 1.988**
Human vs. AI at casual restaurants	**t = 4.18, p < .001, d = 0.618**	**t = 5.25, p < .001, d = 0.776**	**t = 8.03, p < .001, d = 1.187**	**t = 0.77, p = .444, d = 0.113**

Note: Bold indicates significant results (p<.05).

6.4.1. Perceived food quality as a mediator

A moderated mediation analysis and boot-strapping with 5,000 samples showed a significant index of moderated mediation (index = -.376, 95% CI [-.665, -.110]). Follow-up analysis revealed that the indirect effect in the condition of luxury restaurants was significant (B = -.882, SE = .123, 95% CI [-1.143, -.652]), whereas that in the condition of non-luxury restaurants was relatively diminished (B = -.506, SE = .095, 95% CI [-.692, -.322]), suggesting that especially in the context of luxury restaurants, foods cooked by AI negatively influenced consumers' expectations for food quality, in turn decreasing the visit intention to the restaurant. These results support H3a. Full results of the moderated mediation analysis are reported in Figure 4 and Appendix Table in Supplementary Material.

6.4.2. Perceived service quality as a mediator

Regarding the analysis on food quality, we conducted a moderated mediation analysis using service quality instead of food quality as the mediator (see Figure 8 and Table 1 for full results). Boot-strapping with 5,000 samples indicated a significant index of moderated mediation (index = -.337, 95% CI [-.587, -.110]). Follow-up analysis revealed that the indirect effect in the condition of luxury restaurants was significant (B = -.980, SE = .132, 95% CI [-1.242, -.722]), whereas that in the condition of casual restaurants was significant but diminished (B = -.642, SE = .091, 95% CI [-.827, -.472]). Thus, consistent with the results of the food quality, we found that in the context of luxury restaurants, foods cooked by AI decreased consumers' intention to visit the restaurant through negative expectations for service quality. These results support H3b.

6.4.3. Perceived ambience quality as a mediator

We performed a moderated mediation analysis with the same model as those used in the previous analyses, which included ambience quality instead of food or service quality as the mediator (see Figure 8 and Table 1 for full results). Consistent with the results of other mediators, boot-strapping with 5,000 samples showed a significant index of moderated mediation (index = -.624, 95% CI [-.877, -.400]). In the condition of luxury restaurants, ambience quality mediated the relationship between service staff and visit intention (B = -.675, SE = .109, 95% CI [-.899, -.473]). Unlike other mediators, in the condition of non-luxury restaurants, there was no significant indirect effect of service provider through ambience quality (B = -.052, SE = .069, 95% CI [-.191, .083]). While statistical significance of indirect effect was slightly different among the dimensions of restaurant's quality, the results consistently showed that in the condition of non-luxury restaurants, the indirect effects of service provider on visit intention through restaurant's qualities were smaller compared to the condition of luxury restaurants. Hence, it can be concluded that H3c was also supported.

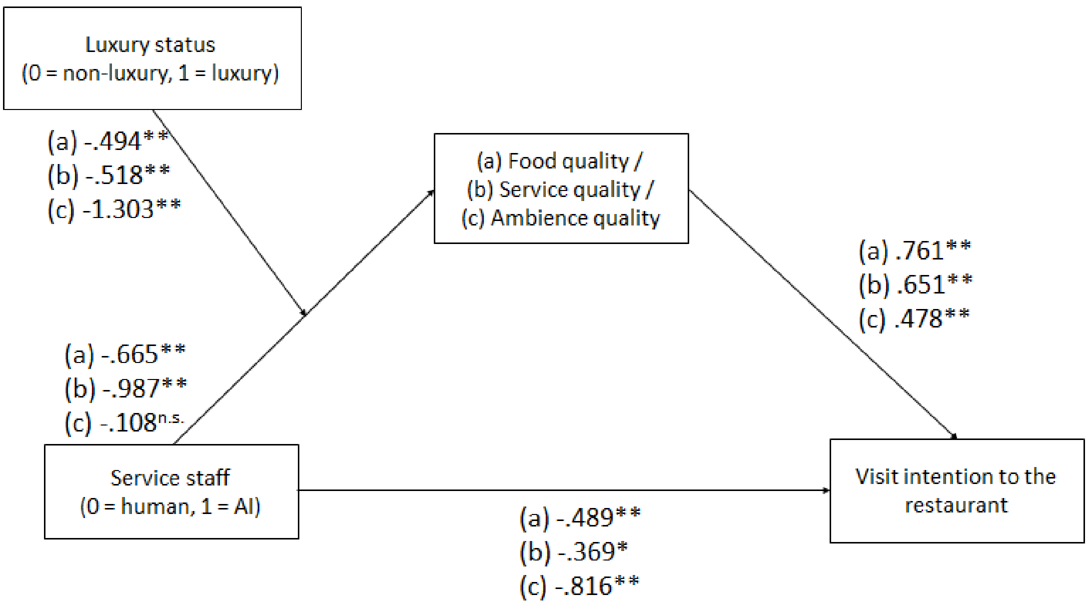


Figure 4. Results of the moderated mediation analysis.
Note. Numbers indicate unstandardized coefficients.
**: 1% level, *: 5% level.

7. Discussion

7.1. Summary of findings

Across four studies, we investigated the role of restaurant service provider (AI vs. humans) on consumers' evaluations of the restaurants. The results demonstrated that consumers evaluated more negatively the restaurants in which AI is the service provider (Study 1). The effects of AI were higher in luxury restaurants compared to non-luxury, casual dining (e.g., fast food, casual restaurants) (Studies 2-4). Especially regarding luxury restaurants, foods cooked by AI negatively influenced consumers' expectations of three dimensions of restaurants' quality (food, service, and ambience quality), in turn decreasing consumers' intention to visit the restaurant (Study 4).

7.2. Theoretical implications for using AI in food services

Our findings support and contribute to the existing framework for using AI in services (Huang & Rust, 2021). The theoretical framework indicates that consumers respond differently to the use of AI, depending on the types of services and the extent to which they include cognitive-analytical or emotional-social elements (Huang & Rust, 2021; also see Wirtz et al., 2018). Specifically, it has been observed that consumers respond more negatively to AI in hedonic services than in utilitarian or mechanical services (Huang & Rust, 2021; Wirtz et al., 2018). In line with the theoretical framework, one study has shown that AI is more associated with utilitarian rather than hedonic consumption (Longoni & Cian, 2020). However, to our knowledge, no research has investigated how consumers respond to hedonic or utilitarian-related services in the food domain. This study fills this gap by focusing on the context of food services and examining the effects of using AI as a service provider on consumer evaluation. Specifically, this study relies on the theoretical framework for using AI in different services (Huang & Rust, 2021; Wirtz et al., 2018) and the literature on luxury consumptions (e.g., Holmqvist et al., 2020), our results extend the previous findings and demonstrate that negative effects of AI on consumer evaluations are augmented in food services involving more hedonic value (i.e., luxury restaurants).

7.3. Theoretical implications on research on hospitality management and AI

The findings contribute to research on hospitality management and AI. Several studies investigated the role of AI in hospitality management (Ho et al., 2020; S. Kim et al., 2021; Li et al., 2019; Lu et al., 2019; Prentice et al., 2020; Seyitoğlu & Ivanov, 2020b) However, most studies have investigated the role of AI in the hotel industry. Fewer research has investigated the role of AI in restaurant settings. The importance of this issue has been increasing during the COVID-19 pandemic (Bucak & Yiğit, 2021). It has been predicted that the use of AI (e.g., robots) in kitchens will increase after the COVID-19 outbreak (Bucak & Yiğit, 2021). This research has dealt with the timely issue by combining research on AI, restaurant service, and consumer behaviour, and our findings add to the existing knowledge of hospitality management and AI.

7.4. Theoretical implications on research on halo/horn effects and restaurant quality

Our findings demonstrated that the effect of the service provider (i.e., robot kitchen staff) on behavioural intention to restaurants was mediated by restaurant quality. Previous research on restaurants service indicates that food, service, and ambience quality lead to behavioural intention to restaurants (i.e., visit intention) (e.g., Hwang & Ok, 2013; Lee & Hwang, 2011; Ryu & Han, 2010). Our study revealed that the presence of cooking staff with AI decreased not only expectations of food quality, but also those of service and ambience qualities, in turn decreasing behavioural intention to restaurants. Together, the findings suggest the 'halo (horn) effect' of the service provider and demonstrate that the use of AI for food preparation is lower in food quality and the food-unrelated qualities, and then diminishes behavioural intention to restaurants.

7.5. Practical implications

Our study provides practical implications for managers in the restaurant industry. Some innovative restaurants have already taken advantage of AI and robots at various steps of the service process, such as cooking and serving (Berezina, Ciftci, & Cobanoglu, 2019; Oracle, 2019). Indeed, there is no doubt that these technologies will benefit restaurants in terms of efficiency, productivity, and accuracy of their operation. However, the results of our study suggest that using new technologies does not always benefit all types of restaurants. Our findings suggest that consumers evaluated the restaurant more positively when realizing that humans prepared food at a luxury (vs. non luxury) restaurant, though it is also worth mentioning that food prepared by AI was also evaluated above the centre of preference rating. Therefore, luxury restaurants should be careful about introducing new technologies like AI. Rather, there is the possibility that the restaurants are evaluated more favourably by appealing the 'humanity' or 'sense-of-homemade' of the cooking process to their customers. However, this study also revealed that in the condition of non-luxury dining (i.e., fast food, casual restaurants), there was not a significant difference in the intention to visit between AI and human kitchen staff with some exceptions. This result provides managers in the restaurant industry with important implications. Generally, casual restaurants work hard to reduce costs, including labour costs and operating costs, based on the business model of 'small profits and quick returns'. Hence, by utilizing AI more proactively, they can improve the efficiency and profitability of their operation without hurting their customers' images and visit intentions.

7.6. Limitations and future research

This study has limitations. First, this study recruited only Japanese and UK participants. Past studies show that there are cultural differences in how humans evaluate the likability of AI, such as social robots (Li et al., 2010). For example, German participants show lower ratings of likeability, engagement, trust, and satisfaction scores to robots than Chinese and Korean participants (Li et al., 2010). Thus, the effects of the service provider with AI on restaurant ratings might be distinct across cultures. Actually, the results of Study 3 indicate that the effects of AI on food preferences differ in Japan and the UK, especially in non-luxury restaurants. In Japan, the type of provider (AI, humans) does not affect the food preferences; however, in the UK, using AI (vs. humans) reduces the food preferences. Considering many examples of restaurants utilising AI in Japan (Kelly & Tomoshige, 2020), consumers who live in Japan might be more driven towards technology adoption and readiness than those who live in the other countries. The food/restaurants provided by AI chefs might be more negatively evaluated by those who live in countries where the technology adoption and readiness are relatively low. Future research is needed to investigate whether these findings will be applicable to other countries and cultures. Second, we did not include the appearance of the service provider with AI staff. Previous research has shown that consumers respond differently to service robots depending on their appearance. For example, three types of robot appearances (anthropomorphic, zoomorphic, machinelike) lead to different likability ratings (Li et al., 2010). Therefore, future research needs to demonstrate whether the appearance of AI kitchen staff influences the degree of consumers' preferences for both luxury and casual restaurants.

Another limitation is that there seem to be differences between luxury and non-luxury restaurants in how consumers can see the cooking area. Consumers might not be able to see them and identify who the chef is in a luxury restaurant, even though the identity might be notified in other ways (e.g., advertisements, restaurant websites). In contrast, in non-luxury restaurants (e.g., fast-food ones), the cooking area often seems visible, and consumers easily find out who works there. Our research did not consider the possibility and future research should consider it. The fourth limitation is the gender proportion of our participants. Our participants include more males than females.

To address the issue, we conducted exploratory analyses by dividing the dataset into males and females. As a result, our main findings remain in the data of both males and females (see Appendix in Supplementary Material). Regardless of whether the dataset is males or females, AI (vs. humans) decrease consumer preferences and the effects of AI (vs. humans) are more prominent at luxury status than at non-luxury status, as indicated by the effect sizes. This suggests that our findings might not be affected by the skewed gender ratio. Nevertheless, further research should be needed to confirm the generalisability of our findings. Moreover, our online samples might be familiar with and some knowledge of technology, which possibly influenced our findings. Further research needs to be conducted by recruiting larger and more representative samples.

7.7. Conclusions

In conclusion, this research investigated the effects of using AI on consumers' evaluation of restaurants. Consumers evaluated the restaurants negatively where the service provider of AI (vs. humans) works. The effects of AI were higher in luxury restaurants compared to in casual dining. These findings reveal the role of AI in hospitality management and provide practical insight on how to introduce AI in restaurant industries.

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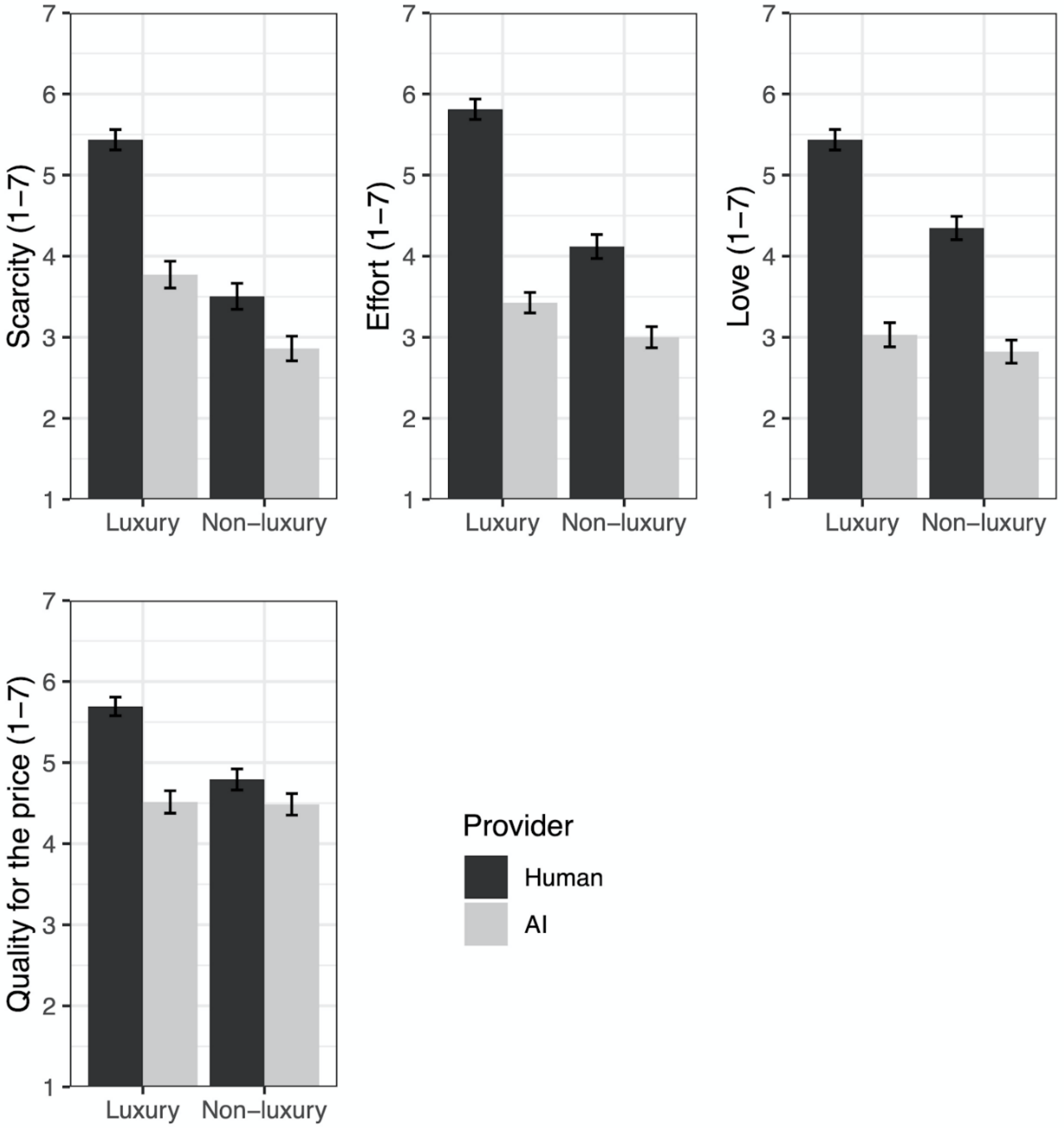
Supplementary Material

Appendix A. Procedure and results of additional dependent variables in Study 1.

Participants in Study 1 were indicated and asked the following: ‘We are considering creating luxury [cheap] products and services made by artificial intelligence [humans]. Examples are restaurant menu, clothing, and medical services. Please answer perceived scarcity, love, effort, and quality for the price of the products and services. The order of items (e.g., scarcity, love) was randomized within participants. The responses were recorded on a 7-point Likert-scale (1: not at all, 7: very much). The results of additional dependent variables are shown in Appendix.



Appendix Figure A. Influences of the service provider (AI, humans) and restaurant type (luxury, non—luxury) on the perception of scarcity, love, effort, and quality for the price. The Likert rating scale ranged from 1–7 ('not at all' to 'very much'). Error bars represent standard errors of the mean.

Scarcity

The analysis revealed main effects of service provider ($F_{1,100}$ = 47.26, p < .001 η^2_p = 0.32) and restaurant type ($F_{1,100}$ = 108.53, p = .001, η^2_p = 0.520). The analysis showed significant interactions between service provider and restaurant type ($F_{1,100}$ = 21.79, p < .001, η^2_p = 0.179). Post hoc comparisons revealed that human (vs. AI) staff increased the perceived scarcity for both luxury goods/services (M_{AI}= 3.77 ± 1.66, M_{human}= 5.44 ± 1.25, $t_{1,100}$ = 7.01, p < .001, d = 1.26) and non-luxury goods/services (M_{AI}= 2.86 ± 1.52, M_{human}= 3.51 ± 1.60, $t_{1,100}$ = 2.71, p = .008, d= 0.36)

Love

The analysis revealed main effects of service providers ($F_{1,100}$= 128.91, p < .001 η^2_p= 0.563) and restaurant type ($F_{1,100}$= 38.87, p < .001, η^2_p= 0.280). The analysis showed significant interactions between service provider and restaurant type ($F_{1,100}$= 23.87, p < .001, η^2_p= 0.193). Post hoc comparisons revealed that human (vs. AI) staff increased the perceived love for both luxury goods/services (M_{AI}= 3.03 ± 1.50, M_{human}= 5.44 ± 1.26, $t_{1,100}$ = 9.828, p < .001, d= 1.840) and non-luxury goods/services (M_{AI}= 2.82 ± 1.42, M_{human}= 4.35 ± 1.44, $t_{1,100}$ = 6.229, p < .001, d= 0.871)

Effort

The analysis revealed main effects of service providers ($F_{1,100}$= 152.94, p < .001 η^2_p= 0.605) and restaurant type ($F_{1,100}$= 95.54, p = .001, η^2_p= 0.489). The analysis showed significant interactions between service provider and restaurant type ($F_{1,100}$= 43.87, p < .001, η^2_p= 0.305). Post hoc comparisons revealed that human (vs. AI) staff increased the perceived effort for both luxury goods/services (M_{AI}= 3.43 ± 0.16, M_{human}= 5.81 ± 1.26, $t_{1,100}$ = 11.91, p < .001, d= 2.017) and non-luxury goods/services (M_{AI}= 3.00 ± 1.30, M_{human}= 4.12 ± 1.47, $t_{1,100}$ = 5.58, p < .001, d= 0.707)

Quality for the price

The analysis revealed main effects of service providers ($F_{1,100}$= 38.46, p < .001 η^2_p= 0.278) and restaurant type ($F_{1,100}$= 26.79, p < .001, η^2_p= 0.211). The analysis showed significant interactions between service provider and restaurant type ($F_{1,100}$= 28.34, p < .001, η^2_p= 0.227). Post hoc comparisons revealed that human (vs. AI) staff increased the perceived quality for the price for luxury goods/services (M_{AI}= 4.52 ± 1.39, M_{human}= 5.69 ± 1.15, $t_{1,100}$ = 6.958, p < .001, d= 0.97). In contrast, humans and AI did not differ in terms of the perceived quality for non-luxury goods/services (M_{AI}= 4.49 ± 1.33, M_{human}= 4.79 ± 1.30, $t_{1,100}$ = 1.813, p = .073, d= 0.19).

Appendix Figure B. The items for three restaurant qualities (food, service, ambience quality) in Study 4.

How do you think about luxury [casual] restaurants where the food is made by AI (artificial intelligence) [humans]?

	Not at all 1	2	3	Neutral 4	5	6	Very much 7
Tastiness of the food	○	○	○	○	○	○	○
Freshness of the food	○	○	○	○	○	○	○
Visual appeal of the food	○	○	○	○	○	○	○
Variety of the food menu	○	○	○	○	○	○	○
Friendliness of the employees	○	○	○	○	○	○	○
Responsiveness to check and order	○	○	○	○	○	○	○
Trustworthiness of the employees	○	○	○	○	○	○	○
Competence of the employees	○	○	○	○	○	○	○
Appeal of interior design	○	○	○	○	○	○	○
Stylish ambience	○	○	○	○	○	○	○
Comfortable ambience	○	○	○	○	○	○	○
Fancy and elegant ambience	○	○	○	○	○	○	○

Appendix Table A. Descriptive statistics of the results in Study 4.

	Visit intention	Food quality	Service quality	Ambience quality
Human	5.40 (1.15)	5.45 (0.85)	5.17 (0.81)	4.93 (1.17)
AI	4.23 (1.40)	4.54 (0.94)	3.93 (0.91)	4.17 (0.99)
Luxury	4.83 (1.51)	5.22 (1.05)	4.74 (1.15)	4.97 (1.17)
Non-luxury	4.79 (1.29)	4.77 (0.88)	4.36 (0.92)	4.13 (0.95)
Human-luxury	5.60 (1.15)	5.8 (0.69)	5.50 (0.75)	5.67 (0.83)
AI-luxury	4.07 (1.42)	4.64 (1.03)	3.99 (0.96)	4.26 (1.03)
Human-non-luxury	5.18 (1.12)	5.10 (0.84)	4.85 (0.74)	4.19 (0.97)
AI-non-luxury	4.39 (1.35)	4.44 (0.79)	3.86 (0.83)	4.08 (0.93)

Note: Each cell represents mean and standard deviation.

Appendix Table C. Results of the moderated mediation analysis

(a) Food quality

Independent variable	Dependent variable	B	SE	t	p	LLCI	ULCI
Service provider	Food quality	-.665	.127	-5.249	<.001	4.937	5.273
Restaurant type		.697	.121	5.775	<.001	.460	.934
Service provider x restaurant type		-.494	.175	-2.827	.005	-.837	-.150
Service provider	Visit intention	-.489	.124	-3.931	<.001	-.734	-.244
Food quality		.761	.062	12.220	<.001	.639	.883

(b) Service quality

Independent variable	Dependent variable	B	SE	t	p	LLCI	ULCI
Service provider	Service quality	-.987	.123	-8.032	<.001	-1.229	-.745
Restaurant type		.645	.117	5.508	<.001	.415	.875
Service provider x restaurant type		-.518	.170	-3.056	.002	-.851	-.185
Service provider	Visit intention	-.369	.145	-2.541	.012	-.654	-.083
Service quality		.651	.068	9.515	<.001	.516	.785

(c) Ambience quality

Independent variable	Dependent variable	B	SE	t	p	LLCI	ULCI

Service provider	Ambience quality	-.108	.140	-.766	.444	-.384	.169
Restaurant type		1.486	.134	11.100	<.001	1.223	1.749
Service provider x restaurant type		-1.303	.194	-6.726	<.001	-1.684	-.922
Service provider	Visit intention	-.816	.127	-6.451	<.001	-1.065	-.567
Ambience quality		.478	.055	8.713	<.001	.370	.586

Note. LLCI and ULCI mean lower and upper levels of the confidence interval, respectively.

Appendix Tables D: Effects of provider and status on the desirability of products/services in males and females (Study 1).

	Effect	F	df	p	η^2_p
Males	Provider	30.440	69	<.001	.306
	Status	2.615	69	.110	.037
	Provider*Status	33.386	69	<.001	.326
	Effect	F	df	p	η^2_p
	Provider	15.455	30	<.001	.340
Females	Status	2.950	30	.096	.090
	Provider*Status	23.157	30	<.001	.436

Post-hoc comparisons

		Difference (AI - Human)	SE	t	df	p	d
Males	Luxury	-1.800	0.203	-8.857	69	<.001	-1.722
	Non-luxury	0.214	0.203	1.054	69	.295	.153
		Difference (AI - Human)	SE	t	df	p	d
Females	Luxury	-2.258	0.319	-7.076	30	<.001	-2.069
	Non-luxury	0.484	0.319	1.516	30	.140	.328

Appendix Tables E: Effects of provider and status on the intention to eat the food in males and females (Study 2).

	Effect	F	df	p	η^2_p
Males	Provider	41.454	63	<.001	.397
	Status	6.053	63	.017	.088
	Provider*Status	26.659	63	<.001	.297
	Effect	F	df	p	η^2_p
Females	Provider	32.590	35	<.001	.482
	Status	12.368	35	.001	.261
	Provider*Status	19.588	35	<.001	.359

Post-hoc comparisons		Difference (AI - Human)	SE	t	df	p	d
Males	Luxury	-1.438	0.209	-6.866	63	<.001	-1.196
	Non-luxury	-0.469	0.209	-2.239	63	.029	-.291
		Difference (AI - Human)	SE	t	df	p	d
Females	Luxury	-1.667	0.251	-6.636	35	<.001	-1.524
	Non-luxury	-0.361	0.251	-1.438	35	.159	-.245

Appendix Tables F: Effects of provider and status on the intention to eat the food in males and females (Study 3A).

	Effect	*F*	df	*p*	η^2_p
Males	Provider	18.771	116	<.001	.139
	Status	1.339	116	.250	.011
	Provider*Status	47.344	116	<.001	.290
	Effect	*F*	df	*p*	η^2_p
Females	Provider	13.685	79	<.001	.148
	Status	0.043	79	.837	.001
	Provider*Status	46.448	79	<.001	.370

Post-hoc comparisons		Difference (AI - Human)	SE	*t*	df	*p*	*d*
Males	Luxury	-1.776	0.238	-7.470	232	<.001	-2.651
	Non-luxury	0.079	0.238	0.333	232	.739	.088
		Difference (AI - Human)	SE	*t*	df	*p*	*d*
Females	Luxury	-1.956	0.311	-6.280	158	<.001	-2.665
	Non-luxury	-0.122	0.311	-0.393	158	.695	-.124

Appendix Tables G: Effects of provider and status on the intention to eat the food in males and females (Study 3B).

	Effect	*F*	df	*p*	η^2_p
Males	Provider	23.400	50	<.001	.319
	Status	3.146	50	.082	.059
	Provider*Status	23.835	50	<.001	.323
	Effect	*F*	df	*p*	η^2_p
Females	Provider	124.903	145	<.001	.463
	Status	5.696	145	.018	.038
	Provider*Status	29.114	145	<.001	.167

Post-hoc comparisons		Difference (AI - Human)	SE	*t*	df	*p*	*d*
Males	Luxury	-2.850	0.433	-6.576	100	<.001	-3.476
	Non-luxury	-0.840	0.433	-1.938	100	.055	-.757
		Difference (AI - Human)	SE	*t*	df	*p*	*d*
Females	Luxury	-3.098	0.251	-12.362	290	<.001	-3.859
	Non-luxury	-1.712	0.251	-6.829	290	<.001	-1.591

Appendix Tables H: Effects of provider and status on the intention to visit in males and females (Study 4).

	Effect	*F*	df	*p*	η^2_p
Males	Provider	45.421	219	<.001	.172
	Status	0.072	219	.789	.000
	Provider*Status	0.429	219	.513	.002
	Effect	*F*	df	*p*	η^2_p
Females	Provider	28.823	151	<.001	.160
	Status	0.383	151	.537	.003
	Provider*Status	13.772	151	<.001	.084

Post-hoc comparisons		Difference (AI - Human)	SE	*t*	df	*p*	*d*
Males	Luxury	-1.271	0.239	-5.312	219	<.001	-1.327
	Non-luxury	-1.046	0.247	-4.237	219	<.001	-.814
		Difference (AI - Human)	SE	*t*	df	*p*	*d*
Females	Luxury	-1.852	0.276	-6.705	151	<.001	-1.979
	Non-luxury	-0.338	0.300	-1.126	151	.262	-.268