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Chatbot usage in restaurant takeout orders: A comparison study of three ordering methods

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ABSTRACT

The purpose of this study was to explore customers' perceptions and behaviors when using chatbots in restaurant takeout orders. Built on the social presence theory, this study conducted a lab experiment to examine and compare three ordering methods in quick-service and full-service restaurants. Results revealed that phone ordering and online ordering were both better than chatbot ordering in terms of satisfaction and behavioral outcomes. The phone ordering method elicited best social presence and cognitive attitudes, while the online ordering method generated highest order amounts. Chatbot ordering is better suited for use in quick-service restaurants due to their simpler menus. In terms of order items, chatbot method was used for simple menu items and core products, phone method for specials and more complicated items, while online method for more expensive items and add-ons. The findings offer new insight for restaurant practitioners into designing and adopting chatbots.

1. Introduction

As more and more Americans are cooking less at home due to the increase number of family members and the pressure to balance work and family lives (Gregoire, 2013), the restaurant industry witnesses a trend of increasing delivery and takeout business. According to a recent study, 60% of U.S. consumers ordered delivery or takeout once a week and 59% of restaurant orders from millennials were takeout or delivery (Everett, 2019). Quick-service restaurants used to be the primary provider for takeout or delivery food orders. However, with the increased home meal replacement programs (Gregoire, 2013), more full-service restaurants are offering takeout orders that customers can call in advance or order online that foods will be ready and be quickly purchased.

Digital ordering was a major contributor to the growth of delivery and takeout business, with a 300% growth rate than dine-in traffic since 2014 (NPD, 2018). Online ordering and mobile apps ordering were the two main components of restaurant digital ordering system (Kimes, 2011a). Compared to phone ordering, digital ordering offers potential benefits to restaurants including increased revenue, improved capacity management, improved productivity, and improved transactional marketing and customer relationship management (Kimes & Laqué, 2011).

Spurred by the recent developments in artificial intelligence (AI), chatbots represent a potential shift in how customers interact with the restaurant industry digitally (Brandtzaeg & Følstad, 2017). Chatbots are "machine conversation systems that interact with human users via natural conversational language" (Shawar & Atwell, 2005, p. 489). Chatbots are developed to evoke humanlike interactions through text or voice using mobile messaging applications, such as Slack, Facebook Messenger, Twitter, SMS, or standalone chatbots such as Amazon's Alexa and Google's Google Home (Brandtzaeg & Følstad, 2017). With the selected skills installed, chatbots are now able to help customers find restaurants, make reservations, place takeout orders, and even checkout the dress code of the restaurants (Barack, 2018).

A recent study indicated that 56% of chatbot users were interested in ordering meals from restaurants using chatbots, while 34% had already ordered at least one meal (Atkinson, 2018). As chatbots can be easily integrated with any restaurant's existing communication system, including POS, websites, or mobile apps, they present a promising expansion to the current restaurant digital ordering system (Savjani, 2016). For restaurant owners, chatbots share all the operational benefits offered by digital ordering methods such as increased revenue, improved productivity, and lowered labor costs. In addition, chatbots also have communication advantage over online and mobile app ordering methods as they allow customers to skip steps in the process or order as organically as they would with a server (Hennessy, 2016).

Literature revealed that restaurant customers' perceptions on digital

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ordering varied. Some expressed higher satisfaction due to an increased level of control, while others were disappointed because of technology anxiety and lack of human interaction (Kimes, 2011a). With the promising future of adding chatbots to the current digital ordering system, it is critical for restaurant owners and managers to understand customers' attitude, satisfaction, and behavior when using chatbots for food ordering. Literature on human interactions has existed in the field of social sciences for decades, explaining how and why human beings act and react to one another. With the development of computerized technologies, researchers have explored human-computer interaction (HCI) and human-robot interaction (HRI) by mimicking human-human interaction (HHI), focusing on social presence perceived by human beings while interacting with another agent (Fiore et al., 2013; Von der Puetten, Krämer, Gratch, & Kang, 2010). However, academic research on the application of chatbots in the hospitality industry is largely lacking, especially empirical studies (Kuo, Chen, & Tseng, 2017). This study intends to address this research gap by comparing the performance and customer perceptions of chatbots with other ordering methods in restaurant takeout orders based on the social presence theory. Specially, with the increasing number of full-service restaurants entering the digital ordering market, it will be meaningful to compare these ordering methods in quick-service restaurants and full-service restaurants. According to the contingency theory, organizational effectiveness is determined by the consistency of organizational characteristics, organizational types, and external contingency factors (Scott, 1981). Thus, this study aims to apply the contingency theory as the theoretical foundation to explore the fits between restaurant types (i.e., quick-service, full-service) and ordering methods.

Therefore, this study explores and compares social presence resulting from human-human interaction (HHI), human-computer interaction (HCI), and human-robot (chatbot) interaction (HRI) with the application of social presence theory in the context of the three food ordering methods: phone ordering, online ordering, and chatbot ordering. In addition, the study investigates and compares customer perceptions and behaviors when using the three different ordering methods. Specifically, this study sets forth the following objectives: (1) to compare the effects of the ordering method (interaction mode) and restaurant type on social presence, attitudes, satisfaction, and behavioral outcomes; (2) to identify order item preferences when using the three ordering methods; and (3) to provide suggestions for restaurants to leverage chatbots to improve customer service and to increase sales. As this study emphasizes human-centered experiences and the social characteristics of chatbots, the findings are expected to shed light on the future utilization of chatbots in the hospitality industry.

2. Literature review and hypotheses development

2.1. HRI and chatbot research in hospitality

In response to the emergence and prevalence of socially interactive robots, a growing body of research has explored the impacts of implementing service robots in various work environments (Hancock et al., 2011; Kwak & Park, 2012; Tung & Au, 2018). Hospitality researchers have noted the importance of HRI in their studies and emphasized that HRI is a critical robotic element in the hospitality industry as customers interact and co-create value and experience with service robots (Choi, Choi, Oh, & Kim, 2019; Murphy, Hofacker, & Gretzel, 2017; Pan, Okada, Uchiyama, & Suzuki, 2015; Qiu, Li, Shu, & Bai, 2020). With the increasing application of service robots in the hotel industry, researchers had studied customers' experiences with HRI by analyzing online reviews of four hotels that use robots (Tung & Au, 2018). Recently, a growing number of studies emerged focusing on HRI in the hospitality industry, these studies had examined the relationship building between customers and robots (Qiu et al., 2020), conceptualized the "trust" aspect of HRI (Simon, Neuhofer, & Egger, 2020), and found strategies to understand and improve HRI in different aspects (Collins, 2020; Kervenoael, Hasan, Schwob, & Goh, 2020; Murphy, Gretzel, & Pesonen, 2019). In addition, researchers stressed the importance of HRI as it influences customers' acceptance and future development of service robots (Lin, Chi, & Gursoy, 2019; Pan et al., 2015).

Chatbots, also be called as machine conservation system, dialogue system, and chatterbot, were first designed in early 1960s to interact with users in human-like natural languages (Ciechanowski, Przegalinska, Magnuski, & Gloor, 2019). Today, the chatbot systems are not restricted to mimic human-like conservations, but also designed to be accessed through virtual agents such as Amazon Alexa or Google Assistant, with applications in the fields of businesses, e-commence, information retrieving, education, entertainments, etc. (Ciechanowski et al., 2019). Previous literature on chatbots has emphasized the importance of examining social factors that impact communication and interaction between human and chatbots (Ciechanowski et al., 2019; Hill, Ford, & Farreras, 2015; Mou & Xu, 2017). In the restaurant food ordering context, understanding human-chatbot interactions becomes even more important as it helps to create better experiences for customers and ultimately to increase sales (Bilgihan & Nejad, 2015; Van Doorn et al., 2017).

As majority of chatbot users are interested in placing food orders through chatbots (Atkinson, 2018), the potentially widespread applications of chatbots may bring additional opportunities and revenues to restaurants adopting the chatbot food ordering platform. However, no empirical study had been conducted, in consumers' perspectives, to explore Chatbot functions when customers placing restaurant food orders. To address the lack of research on AI and robotic applications, especially chatbot applications, in the restaurant industry, this study aimed to explore the impact of chatbots on customers' takeout order experiences through the comparison of the three different ordering methods (phone, online, or chatbots), which correspond with HRI, HCI, and HHI, respectively.

2.2. Social presence theory

Social presence, as postulated by Short, Williams, and Christie (1976), refers to the degree to which a person is perceived as a "real person" when interacting with others in the mediated communication (Gunawardena & Zittle, 1997). In other words, social presence is the presence of human or human-like intelligence in the interaction process (Lee, Peng, Jin, & Yan, 2006). As suggested by the social presence theory, robots with highly human-oriented perceptions were perceived as intelligent "buddies" with whom human beings enjoyed interacting with (Lin & Schmidt, 2015). In addition, consumers may treat robots-like humans by forming social perceptions of robots based on their physical traits such as appearance and voice (Dautenhahn et al., 2006; Eyssel, Kuchenbrandt, & Bobinger, 2011).

Some research on social presence focused on its capacity to transmit information through non-verbal cues (e.g., facial expressions), while other studies emphasized the interactivity of the communication media (Hassanein & Head, 2007; Sproull & Kiesler, 1986). Studies on HCI also considered whether such interaction conveys a sense of sociability and human sensitivity (Hassanein & Head, 2007). In the HRI literature, researchers contended that the ultimate goal of designing socially interactive robots was to instill among consumers a strong sense of social presence during HRI (Breazeal, 2004; Fong, Nourbakhsh, & Dautenhahn, 2003; Lee et al., 2006). Social robots were designed to apply social human interaction methods to communicate (Seo, Geiskkovitch, Nakane, King, & Young, 2015), and act like real social actors in order to create a truly social experience for users (Lee et al., 2006). Previously, social presence has been found to play important roles in HCI (Klein, 1999; Lee & Nass, 2004) and HRI processes (Lee et al., 2006). In general, HRI was believed to be more socially interactive than HCI because it has better artificial intelligence (AI) engines and involves more human sensory systems (Lee et al., 2006). As the aforementioned studies suggest that different levels of social presence may exist in HHI, HCI, and HRI, the first hypothesis is proposed:

H1 Placing restaurant takeout orders via different methods (phone, online, or chatbot) generates different levels of social presence.

Social presence shows a significant impact on consumers' attitudes. In advertising research, Fortin and Dholakia (2005) found that social presence of HCI positively affect customers' cognitive and affective attitudes towards the web-based ad. In online shopping context, previous literature revealed that higher levels of perceived social presence led to more favorable consumer attitudes (Daliri, Rezaei, & Ismail, 2014; Hassanein & Head, 2007). In restaurant research, Kimes (2011a) demonstrated that different food ordering methods though online platforms (HCI) and phone calls (HHI) evoked different attitudes among consumer. Although chatbot ordering method has not been investigated in the context of restaurant takeout orders, social presence theory proposes chatbot ordering method based on HRI may induce different attitude among restaurant customers due to the different levels of social presence. Therefore this study suggests that customers may have different attitudes toward HHI, HCI, and HRI when placing takeout orders and hypothesizes that:

H2 Placing restaurant takeout orders via different methods (phone, online, or chatbot) evokes different attitudes (a. Cognitive; b. Affective) among customers.

Satisfaction is an outcome from the comparison with expectation and expectancy confirmation (Oliver, 1980). Social presence was found to be a strong predictor of satisfaction in different contexts (Gunawardena & Zittle, 1997). In online education research, multiple studies have demonstrated students' satisfaction increased when they perceived higher level of social presence in online courses (Richardson & Swan, 2003; So & Brush, 2008; Zhan & Mei, 2013). Ogara, Koh, and Prybutok (2014) found that social presence had a positive impact on user satisfaction with mobile instant messaging. Researchers on HRI found that people prefer and enjoy interacting with robots with physical embodiments than virtual or telecommunicating agents (Wainer, Feil-Seifer, Shell, & Mataric, 2006). In restaurant context, Kimes' (2011a) revealed that customers showed increased level of satisfaction with online ordering methods. Additionally, as suggested by Lee et al. (2006), HRI was believed to be more socially interactive than HCI with its AI functions. It will be interesting to explore whether chatbots can lead to better customers satisfaction with advanced social interactivity. Therefore, this study proposes that customers may form different satisfaction with HHI, HCI, and HRI when placing takeout orders as the results of different levels of social presence and sets forth the following hypothesis:

H3 Placing restaurant takeout orders via different methods (phone, online, or chatbot) leads to different levels of customer satisfaction.

Finally, social presence generated in HCI and HRI could potentially impact customers' overall user experience, feeling, and further influence their behavioral responses (McNamara & Kirakowski, 2006). In advertising research, Fortin and Dholakia (2005) tested that social presence generated from a web-based ad positively impact customers' purchase intention. In online shopping context, Daliri et al. (2014) revealed that higher levels of perceived social presence led to higher online shopping intention. Gefen and Straub (2003) also found that consumers' perceptions of social presence had a positive impact on their subsequent purchase intentions on travel ecommerce websites. In restaurant context, Kimes (2011a) reported increases in average check amounts using online ordering methods. Based on social presence theory, the current study proposes that customers may have different behavioral responses with interacting with HHI, HCI, and HRI when placing takeout orders due to different levels of social presence. It is hypothesized that:

H4 Placing restaurant takeout orders via different methods (phone, online, or chatbot) results in different behavioral outcomes (a. Order time; b. Order amount).

2.3. Contingency theory

As the dominant paradigm of organizational structural theories in the 1970s, contingency theory emphasizes on the impact of contingency factors on the best way of organizational structure (Pennings, 1975). The key concept in the contingency theory is fit, referring to the match between organizational structure and its internal and external situations (Drazin & Van de Ven, 1985). Contingency theory states that organizational effectiveness is achieved by matching organizational characteristics to organizational types and external contingency factors (Scott, 1981). The fit emphasized in contingency theory involves environment, technology, and task factors to explain how the organizational outputs are contingent upon the internal operations as well as the external environmental contingencies and constraints (Pennings, 1975). Thus, contingency theory tries to predict organizational performance based on the “fit” among operational strategy, organizational structure, and more recently information technology (Keller, 1994). In hospitality and tourism fields, contingency theory has been applied in both organizational behavior and consumer behavior studies. For example, Kang and Brewer (2009) used contingency theory as foundation to explore hotel's adoption of electronic distribution channels. Kim, Chung, Lee, and Preis (2015) applied contingency theory to explain travelers' mobile shopping experience.

This study applies contingency theory as theoretical foundation to explain the fits between restaurant types and ordering methods. Full-service restaurants, by definition, refers to the commercial foodservice operations which provide table services to their customers that usually customers have the opportunity to interact with service personnel (Gregoire, 2013). Quick-service restaurants, however, mostly provide minimized table service that customers are expected to pick up foods themselves (Gregoire, 2013). When ordering food from these two types of restaurants (full-service and quick-service), customers often have different levels of expectations, such as the potential social interactions (Susskind, 2000). According to contingency theory, the fit or match among task, environment, and technology determines operational performance and technology utilization (Khazanchi, 2005). In other words, when customers placing takeout orders, the change of restaurant type as different environment results in fits with different ordering methods as internal operation and thus leads to different operational performance and technology utilization. For example, Jang and Namkung (2009) identified that the emotional experiences elicited by service-specific stimuli played a more important role in full-service restaurants than in quick-service restaurants. In additional, customers usually expect simple and quick orders in quick-service restaurants, while in full-service restaurants, customers pay higher average checks (NPD, 2014) for well-prepared foods and more service interactions (Susskind, 2000). Using contingency theory as a framework, this study proposes that operational performance of takeout orders using different methods, including social presence, customers' attitudes and satisfaction, and behavioral outcomes (e.g., order time, order amount), may vary in different types of restaurants. Thus, hypotheses H_5 to H_8 states:

H5 There are significant interaction effects between the ordering method and restaurant type (quick-service or full-service) on social presence.

H6 There are significant interaction effects between the ordering method and restaurant type (quick-service or full-service) on attitude changes (a. Cognitive; b. Affective) among customers.

H7 There are significant interaction effects between the ordering method and restaurant type (quick-service or full-service) on

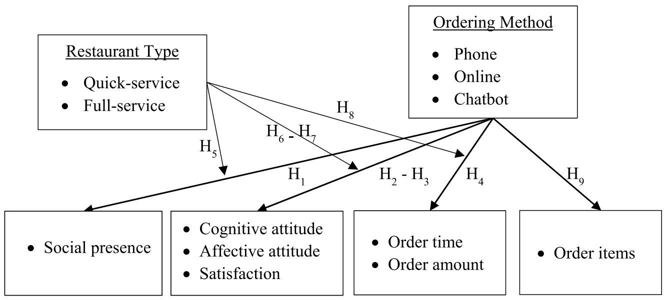

Fig. 1. Hypothesized research model.

customer satisfaction.

H8 There are significant interaction effects between the ordering method and restaurant type (quick-service or full-service) on behavioral outcomes (a. Order time; b. Order amount).

In addition, contingency theory also states that the fit among environment, technology, and task decides how the organization adopt a technology (Keller, 1994; Pennings, 1975). Goodhue and Thompson (1995) also tested that the fit between task and technology would determine the utilization of the technology to a certain degree. Thus, this study proposes that using different ordering methods in takeout orders may lead to different number and types of food items ordered by customers. Thus, it is hypothesized that:

H9 Customers tend to order different food items in takeout orders (a. Quick-service; b. Full-service) when using different ordering methods.

The proposed research model with all hypothesized relationships is presented in Fig. 1.

3. Methodology

3.1. Research design

The study applies a 3 × 2 between-subjects experimental design, where the manipulated factors are ordering method (phone, online, or chatbot) and restaurant type (quick-service or full-service). The three ordering methods were selected to manipulate customer-restaurant interaction type (HHI, HCI, or HRI). HHI is achieved by calling the restaurant directly to place a takeout order with restaurant employees. HCI is achieved by using the restaurant website to place an online takeout order. HRI is achieved by using Amazon's Echo Dot (Alexa) to place a takeout order from the restaurant. Amazon's Alexa was selected since it has the largest market share of the smart speaker market. Alexa used in the study has been preset and linked to researcher's Amazon account to make sure none of the three methods would ask for user account information. Domino's was chosen as the quick-service restaurant sample as it was the first quick-service restaurant to support ordering by Alexa. TGI Fridays was chosen as the full-service restaurant sample because it was the first full-service restaurant to integrate Alexa into the ordering process.

Data collection of this study was conducted between June 2018 and November 2018 in a large public university located in the southern region of the United States. University students were recruited from undergraduate hospitality classes to participate in the experiment in a research lab. Traditional lab studies have used students as pool of valid participants (Druckman & Kam, 2011). In addition, a recent study showed that young adults (aged 18 to 36) with higher education (a bachelor's degree or higher) are heavy adopters of smart speakers (Snook, 2018). Therefore, although with limitations, the student sample selection worked for the study purpose of exploring the acceptance and impact of chatbots on shopping behavior. Researchers made class announcements in six undergraduate classes to recruit volunteers to participate in the study in return for extra credits in class. Participants first made appointments with the researchers and then went to the research lab at set appointment time. Upon arrival, participants were randomly assigned to one of the six groups and placed a test lunch takeout order for two adults. Participants assigned to the two phone groups were asked to select and call one of the provided restaurant phone numbers (TGI Fridays or Domino's) to place a takeout order. Participants assigned to the two chatbot groups were asked to use a lab computer with the restaurant's official website loaded to place a takeout order. Participants assigned to the two chatbot groups were asked to use an Echo Dot with both Fridays and Domino's Alexa skills installed to place a takeout order. While the participants placing the order, the food items they ordered, the total cost of the order, and the time they used to complete the order were all recorded for further analysis. The test orders were cancelled upon completion. Each participant was then asked to complete an online survey on a lab computer.

A total of 153 completed surveys were collected out of 158 participants, resulting in a 96.8% response rate. Each group had 25-27 participants. The minimum sample size calculated using GPower software based on effect size $f^2 = 0.11$ (calculated by SPSS η^2) and $\alpha = 0.05$ is 124. Thus, the study sample size met the minimum required sample size. The sample consists of more females (62.1%) than males (37.9%). The majority of the participants were between the ages of 18 and 24 (82.4%), with some over the age of 34 (5.2%). About half of the participants were White (49.7%), with similar numbers of Black, Asian, and Latino participants (15.0%, 12.4%, and 16.3%, respectively). Almost all of the respondents (96.7%) had placed at least one takeout order from a restaurant. About half had placed takeout orders at least 3 times a month (47.1%), while over 70% had placed takeout orders at least once a month (71.2%), suggesting that the sample could represent the restaurant customer population who place takeout orders.

3.2. Instrument

The survey used in the study consisted of two sections. The first section included demographic questions regarding gender, age, ethnicity, and past restaurant takeout order experience. The second section contained questions to measure social presence, attitudes, and satisfaction. Social presence was measured using five items adopted from Gefen and Straub (2003) on 7-point Likert scales, anchored from *strongly agree* (7) to *strongly disagree* (1). The measures for cognitive attitude and affective attitude both consisted of four pairs of words borrowed from Crites, Fabrigar, and Petty (1994) and measured on seven-point bipolar continuums. The satisfaction measure consisted of two items taken from Ryu, Han, and Kim (2008) on seven-point Likert scales. A pilot study was conducted with a group of 10 undergraduate students. Active undergraduate students enrolled in one hospitality class were asked to voluntarily take the questionnaire online. After finishing the survey, they were asked to provide comments and feedback. The questionnaire was then slightly reworded and modified based on the comments and feedback in the pilot test to ensure that all the questions could be easily understood by undergraduate students. In addition to the questionnaire, two other measures for behavioral outcomes, order time and order amount, were recorded by the researcher during the test food ordering process.

3.3. Data analysis

Data collected in the study were first cleaned and analyzed using Statistical Package for the Social Sciences (SPSS, Version 24.0). Measurement validity was evaluated by conducting principal axis factoring factor analysis with promax rotation on all scale items. Promax oblique rotation was chosen because it allows factors to be correlated (Hair, Black, Babin, & Anderson, 2010), which is typically the case in social science research (Costello & Osborne, 2005). The factor analysis results indicated that two items for the affective attitude construct had cross-loading problems ("pleasant: unpleasant" and "comfortable: uncomfortable") and were thus excluded from further analysis (Hair et al., 2010). All other items had high loadings on the construct they were expected to measure and low loadings on all other constructs. Measurement reliability was assessed by calculating Cronbach's alpha values for each construct, all of which were greater than 0.90. Both validity and reliability tests indicated that the measurements were well designed. The average score of each construct was then calculated for further analysis. Since the two sample restaurants have significantly different menu items and prices, order time and order amount were standardized before merging the two data sets to ensure their comparability. Thus, analyses on order time and order amount were based on standardized scales (z-scores).

Before conducting statistical tests for group differences, independence, homoscedasticity and normality assumptions were checked for all dependent variables. As each case represented a unique respondent, the independence assumption was met. The values for skewness and kurtosis were all within the acceptable limit of ± 2 (Field, 2009), indicating the univariate normality of each variable. The Box's M test indicated a violation of the homoscedasticity assumption. However, considering the relatively equal size of the groups (largest group size/smallest group size < 1.5), this violation had a minimal impact on the results (Hair et al., 2010). Therefore, multivariate analysis of covariance (MANCOVA) and multivariate analysis of variance (MANOVA) were conducted to test all possible main effects and interactions from the two manipulated factors with and without the interference of covariates. A number of covariates that might obscure experimental effects were included in the questionnaire, including gender, age, ethnicity, and past takeout order experience. MANCOVA results demonstrated that none of these covariates had a systematic effect on the results. Thus, the study reported the results of MANOVA for clarity.

Finally, correspondence analysis and chi-square test was utilized to explore whether and how customers order different food items in takeout orders when using the three different ordering methods. Correspondence analysis is a statistical technique used to create perceptual maps where a set of objects and attributes are displayed graphically in a joint space based directly on the association of objects and attributes. In a perceptual map, objects fall in close proximity when they have high association (Hair et al., 2010).

4. Results

4.1. Main effects of ordering method

Multivariate analysis of variance (MANOVA) was conducted to compare social presence, attitudes, satisfaction, and behavioral outcomes among the three ordering methods. The independent variable in the MANOVA was ordering method (phone, online, or chatbot). The six dependent variables as proposed in the research model were: social presence, cognitive attitude, affective attitude, satisfaction, order time, and order amount.

The MANOVA results indicated a significant main effect for ordering method, with Pillai's Trace value of 1.112, $F = 29.82$, $p < 0.001$, partial $\eta^2 = 0.556$. Pillai's Trace was chosen as the statistical measure of the multivariate test, as it is a more robust test statistic when the homogeneity of covariances is violated (Hair et al., 2010). Partial η^2 of the main effect indicated a large effect size ($\eta^2 \geq 0.14$) according to Cohen's (1988) benchmarks.

The univariate test results also showed significant effects of ordering method on all dependent variables except one, affective attitude (Table 1). Therefore, H_1 (ordering method on social presence), H_3 (ordering method on satisfaction), and H_4 (ordering method on order time and order amount) were all fully supported, while H_2 (ordering method on cognitive and affective attitude) was partially supported.

Table 1
Main effects of ordering method.

Variables	Mean (phone)	Mean (online)	Mean (chatbot)	F
Social presence	5.37^a	3.14^b	3.47^b	33.38***
Cognitive attitude	5.63^a	4.53^b	4.38^b	9.32***
Affective attitude	4.54	4.91	4.71	$0.89^{n.s.}$
Satisfaction	5.78^a	6.35^a	4.40^b	27.47***
Order time	-0.50^a	-0.50^a	1.02^b	83.54***
Order amount	-0.40^b	0.52^a	-0.15^b	14.05***

Note: ***$p < 0.001$; **$p < 0.01$; *$p < 0.05$; $^{n.s.}$ $P \geq 0.05$; ^{a,b} The mean scores with different letters (a, b) are significantly different from each other.

The Turkey HSD post hoc test was selected to further analyze group differences, as it is the most common test reported in psychological literature (Warne, Lazo, Ramos, & Ritter, 2012). As shown in Table 1, placing takeout orders over the phone generated better social presence and higher cognitive attitudes than placing takeout orders online or using chatbots. In terms of customer satisfaction, both the phone and online ordering methods led to higher satisfaction than the chatbot ordering method, which was also reflected in the shorter order times. In terms of order amount, the online ordering method resulted in higher order amounts than the other two methods.

4.2. Interaction effects

The MANOVA results also revealed a significant interaction effect between ordering method and restaurant type, with Pillai's Trace value of 0.204, $F = 2.71$, $p < 0.01$, partial $\eta^2 = 0.102$. Partial η^2 of the interaction effect indicated a medium effect size ($\eta^2 \geq 0.06$) according to Cohen's (1988) benchmarks. The univariate test further indicated that there were significant interaction effects on three dependent variables: cognitive attitude, satisfaction, and order time ($F = 3.95$, 4.47, and 4.11, respectively, $ps < 0.05$). Thus, H_5 (interaction effect on social presence) was rejected, H_7 (interaction effect on satisfaction) was fully supported, and H_6 (interaction effect on cognitive and affective attitude) and H_8 (interaction effect on order time and order amount) were partially supported. Fig. 2 shows the mean ratings for the interaction effects. The online and chatbot methods evoked better cognitive attitudes in quick-service restaurants than in full-service restaurants. The chatbot ordering method also elicited more satisfaction with quick-service restaurants than with full-service restaurants. The phone ordering method elicited similar cognitive attitude and satisfaction in both quick-service restaurants and full-service restaurants. In terms of order time, the chatbot ordering method required the longest order time in both quick-service restaurants and full-service restaurants. The phone ordering method was the quickest in quick-service restaurants, while the online ordering method was the quickest in full-service restaurants.

4.3. Order item preferences

To test the last hypothesis H_9, chi-square tests were run to examine the independence between order items and ordering method. The results indicated that participants ordered different food items with both quick-service and full-service restaurants when using the three different ordering methods ($ps < 0.01$), supporting H_9. Thus, correspondence analysis was appropriate for exploring the relationships between attributes (order items) and objects (ordering methods).

As there were only three ordering methods in correspondence analysis, a two-dimensional solution explained 100% of the total variances. Fig. 3 and Fig. 4 display the two perceptual maps generated for quick-service restaurant takeout orders and full-service restaurant takeout orders, respectively. The order item preferences with the quick-

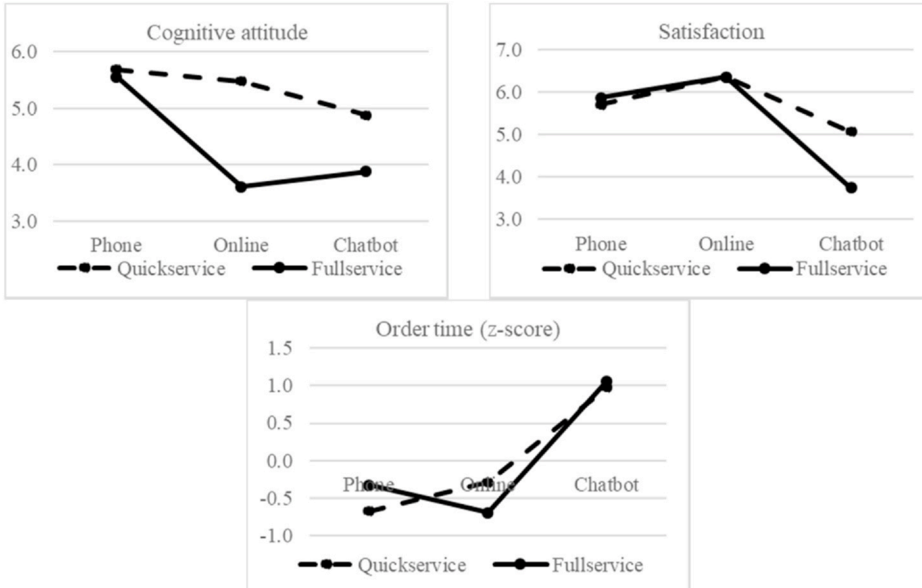

Fig. 2. Interaction effects.

service restaurant are shown in Fig. 3. Customers ordered more pizza and salad when using chatbot and ordered more pizza and pasta when using phone ordering method. Online ordering method created the most diverse food items including chicken, bread, sauce, drink, and desserts. The order item preferences with the full-service restaurant are shown in Fig. 4. Customers ordered more appetizers, burgers, and drink when using chatbot and ordered more soup/salad, chicken, seafood, & pasta, and lunch specials when using phone ordering method. Similar to quick-service, the full-service restaurant also witnessed a more variety of order items when using online ordering method, such as chicken, seafood, & pasta, steaks & ribs, sandwiches, and dessert.

When comparing two perceptual maps, several similarities in order items preferences between quick-service and full-service restaurants were identified. First, chatbot method was used to order simple menu items and core products, for example, pizzas from Domino's or burgers from TGI Fridays. Second, phone method was utilized to order specials and more complicated items, for example, pasta from Domino's or lunch specials from TGI Fridays. Finally, online method was used to order more expensive items and add-ons with the appealing pictures, for example, desserts from both restaurants, chicken from Domino's, or steaks from TGI Fridays. It is interesting to note that some same food item displayed different meanings in different restaurants. For example, when customers order from quick-service restaurants, drink is usually an add-on, while it is considered part of a core meal in full-service restaurants. Therefore, online method for quick-service restaurant produced more drink orders as add-ons while chatbot method for full-service restaurant resulted in more drink orders.

5. Discussion and conclusions

5.1. Discussion

As artificial intelligence (AI) becomes more widely used in the restaurant industry (Fantozzi, 2018), both academics and industry professionals are interested in learning whether and how chatbots can be added to the current digital ordering system in order to provide improved customer experiences. Built on the social presence theory and contingency theory, this study conducted a lab experiment to examine

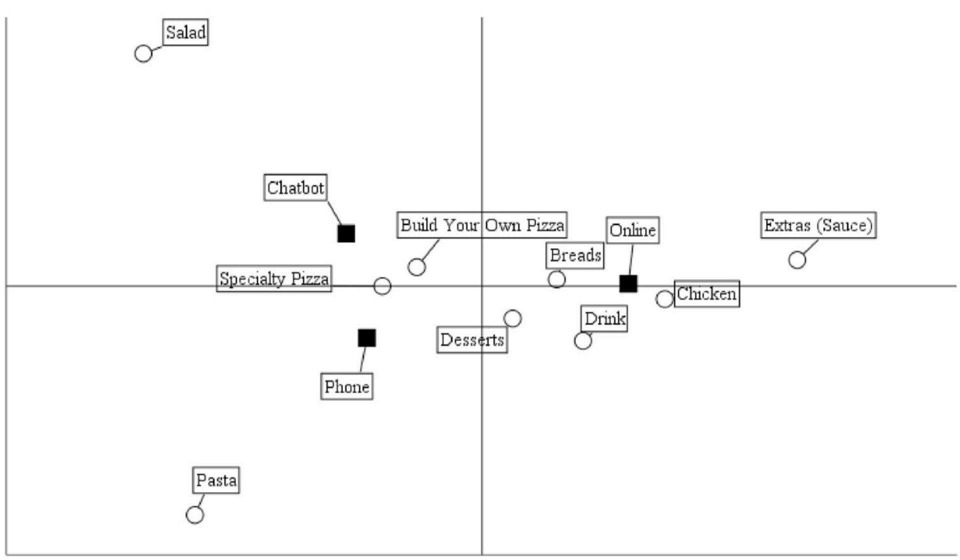

Fig. 3. Perceptual map of item preferences in quick-service takeout orders. Note: black squares represent ordering methods; open circles represent food items.

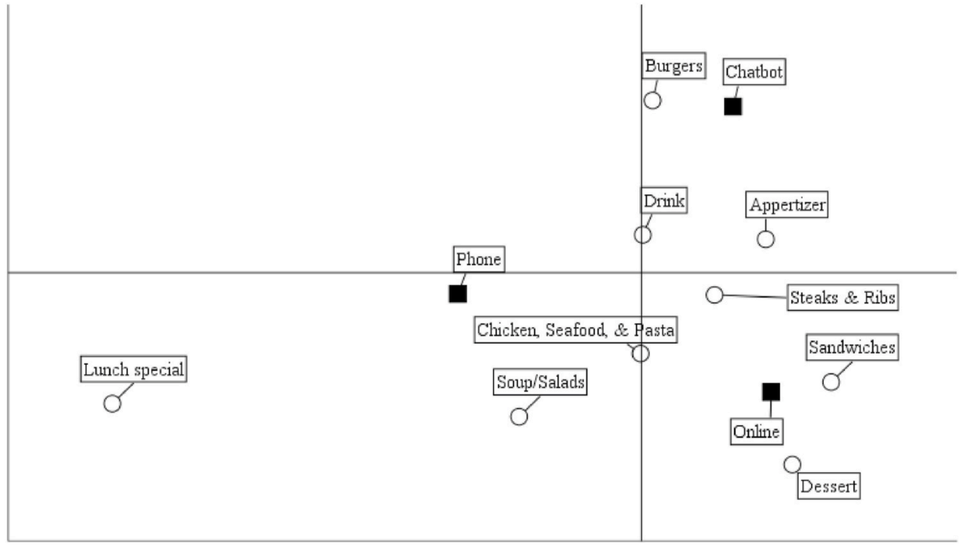

Fig. 4. Perceptual map of item preferences in full-service takeout orders.

the effects of ordering method and restaurant type on social presence, attitudes, satisfaction, and behavior. The findings revealed that the phone and online ordering methods were both better than the chatbot method in terms of both satisfaction and behavior. The phone method generated best social presence, cognitive attitude, and satisfaction, thus reducing order time. The finding of HHI generating higher level of social presence than HRI and HHI is consistent to previous HRI and HHI study findings (Breazeal, 2004). As the idea of social presence in HRI originates in HCI, previous literature also demonstrated that people experience a same level of social presence with HRI and HCI (Westerman, Edwards, Edwards, & Spence, 2018). In addition, the study results also provide empirical support to social presence theory that posits higher social presence lead to better attitude, satisfaction, and behavior (eg. Daliri et al., 2014; Ogara et al., 2014). Besides, although the online ordering method did not have higher level of social presence, it still led to the highest order amounts among the three methods. The results corroborate the findings of Kimes and Laqué (2011) that average restaurant order totals increased after adopting online ordering platforms. Both the performance and customer acceptance of chatbots in placing takeout orders could not compete with the other methods, suggesting that chatbots are not perceived to be as social as human beings. In order to improve chatbot performance, sociability must be improved, and help provided to smooth the ordering process.

The results of the interaction effects between ordering method and restaurant type showed that different ordering methods with quick-service and full-service restaurant did not elicit different levels of social presence. Consumers using the chatbot or online methods to order from quick-service restaurants reported higher cognitive attitudes compared to those who ordered from full-service restaurants. It took the least amount of time to order over the phone from quick-service restaurants and order online from the full-service restaurants. In terms of satisfaction, consumers were most satisfied with online orders for both types of restaurants. However, the performance of chatbots in quick-service restaurants was much closer to the other two ordering methods than in full-service restaurants. This is likely because the menu of quick-service restaurants was easier for AI to understand and manipulate. It is surprising that for full-service restaurants, the online ordering method, instead of the phone method, provided the most satisfaction and shortest ordering time. One possible reason is that when presented a complicated menu offered by full-service restaurants, it is beneficial for customers to view pictures of menu items and have access to ingredient lists that are only available online. The interaction results support the application of contingency theory in this study, indicating that chatbot might be a better "fit" to quick-service restaurants due to the specific customer expectations (Keller, 1994; Susskind, 2000).

The chi-square tests indicated that different ordering methods result in different food items to be ordered in takeout orders for both quick-service and full-service restaurants. It resonated with the findings in Kimes and Laqué's (2011) study that certain types of restaurants were most likely to accept online orders. More interestingly, the study identified similarities in food item selection when using different ordering methods. Chatbot method was used for simple menu items and core products, phone method for specials and more complicated items, and online method for more expensive items and add-ons. The results strengthened the findings of Kimes (2011b) that online ordering presented a good opportunity for upselling due to the increased level of customer control and convenience. It also confirmed de Haan's (2018) findings that chatbots are often used to answer simple requests whereas humans have to take over from chatbots when the situations become more complex.

5.2. Theoretical implications

Despite a growing managerial interest in using AI/robots in hospitality operations, research exploring consumer experiences associated with AI and robotic applications is generally lacking (Tung & Au, 2018). This study responds to their call and makes valuable contributions to the existing hospitality and tourism literature as the first attempt to examine consumers' interactions, attitudes, and behaviors when using chatbots in food ordering processes. As a pioneer study on the application of chatbots in the restaurant industry, this study offers new insight and paves the way for future research. The study innovatively compares the three ordering methods to provide practical implications for the restaurant industry.

From a theoretical standpoint, this study advances the application of the social presence theory by focusing on human-robot interactions. This study expands our understanding of HRI to the hospitality industry by exploring the impact of social presence on customers' ordering experiences. Similar to previous literature, this study found that HRI and HCI generated less social presence than HHI, leading to lower level of attitude. The study provides empirical evidence to support the use of the social presence theory in the food ordering context. A thorough consideration of social presence in this study is beneficial not only to the advancement of theoretical foundation on hospitality virtual experience but also to a better design of new media (e.g., restaurant website) and AI agents (e.g., chatbot, robots).

This study also creatively applies contingency theory as theoretical foundation to explain the interaction effects between restaurant types and ordering methods. Although contingency theory is a classical organizational behavior theory, its application in the hospitality studies, especially in the restaurant context, is still limited. This study contributes to current literature by empirically testing contingency theory in the context of identifying the best ordering method for different types of restaurants. The study results demonstrate the importance of the "fit" between the restaurant type and the ordering method. By applying a social psychology theory (social presence theory) and an organizational theory (contingency theory), the current study illustrates the value of multidisciplinary approach to HRI and social robot studies. Future research may adopt the theoretical framework developed in this study to explore and understand the impacts of AI or robots in different contexts within the hospitality industry.

5.3. Practical implications

A growing number of hospitality organizations are implementing or planning to incorporate chatbot features into their operations. In addition to its theoretical contributions, this timely and informative study may guide hospitality industry professionals through this incorporation process. First, the findings of this study can help restaurant operators understand HRI in food ordering processes and make informed decisions regarding the adoption of chatbots. The results revealed that the chatbot method generated higher customer satisfaction and evoked better cognitive attitudes in quick-service restaurants than in full-service restaurants. As adopting an innovative service technology is usually costly (Bilgihan & Nejad, 2015; Kim, Christodoulidou, & Choo, 2013), restaurant operators should reference these findings when making adoption decisions. Quick-service restaurants with simple menu designs might become early adopters of chatbots Chain quick-service restaurants, due to higher technology budget allocations, may benefit most from investment in chatbots. On the other hand, full-service restaurants with complicated menus and person-centered philosophies should forego adopting chatbots until better AI solutions are developed to improve customer experiences. Restaurant operators should be cautious when making decisions, as the service failures of AI/robots may negatively impact both customer satisfaction and the reputation of hospitality firms (Kim et al., 2013).

Furthermore, as the online ordering method generates the highest satisfaction level for both types of restaurants, restaurant operators should continue optimizing their online ordering features. In particular, full-service restaurants should focus on making it easy for customers to order online, as customers' cognitive attitudes toward online ordering are lower than those toward phone ordering. Quick-service restaurants should work on making one-click purchases available online in order to shorten order times. The most traditional method, phone ordering, elicited the highest cognitive attitudes for both types of restaurants. Restaurant operators should continue training their service staff to provide excellent service over the phone in order to improve customer satisfaction. Customer service training should focus on improving customers' affective attitudes by making the ordering process enjoyable and fun. Full-service restaurants should also train their service staff to be able to take orders effectively in order to reduce order times.

The findings of order item preferences when using different ordering methods have implications for restaurant digital ordering system design. As indicated in the study, chatbots are used to order simpler items and core products while website provides opportunities for selling more expensive items and add-ons. Therefore, the chatbot menu design might be differentiated from website menu. Chatbot menu may focus on the core products of a restaurant and the design of AI should apply fuzzy matching technique in order to understand the order even if the customers couldn't say the correct name. In reality, most customers are not able to remember the exact name of a menu item. For example, in the data collection process, a lot of customers tried to order "pepperoni pizza" from Domino's or "Jack Daniels burger" from TGI Fridays. In this case, fuzzy matching technique would allow chatbots to identify non-exact matches of menu items without asking customers to restate the names and thus streamline the ordering process. On the other hand, the design of online menu might be as detailed as possible with attractive pictures. In addition, the website could also incorporate a good recommendation engine based on past purchasing data for more upselling opportunities. For example, when customers select an entrée item, the website will suggest a dessert or a drink based on which item is chosen. As Amazon reported 35% of revenue generated by its recommendation engine (MacKenzie, Meyer, & Noble, 2013), the restaurant industry could also benefit from developing its own recommendation engine for online ordering.

The results of this study also provide new insight for the design of future chatbots. Just as in the online context, developing social presence of websites can enhance customer's experiences and behavior in online learning and online shopping (Daliri et al., 2014; Hassanein & Head, 2007; Mackey & Freyberg, 2010). Similar suggestions could be provided to improve the future design of social chatbots through enhanced social presence. In the data collection process of the current study, many technological limitations associated with chatbots that require immediate solutions were revealed, including not correctly identifying items and difficulty with canceling items. Thus, chatbot designers must improve the features of chatbots to make them more socially interactive and more efficient when processing food orders. The design of chatbots should also combine better affective features to make the ordering process fun and interesting. For example, the use of humor in customer communication might increase their affective attitudes and lead to greater satisfaction. A successful self-service system like service robots should be able to provide customers with their desired degree of control and interaction (Collier & Sherrell, 2010).

6. Limitations and future research

This study is not without limitations. The current study used undergraduate students as the study sample. Research in the engineering field revealed that an individual's cultural background, age, gender, and educational background may have an impact on the HRI relationship (Li, Rau, & Li, 2010). Future research may include participants with various cultural and demographic backgrounds to explore other factors that may impact customers' ordering experiences using chatbots. As an early exploratory attempt, this study only investigated the effects of chatbots on behavior outcomes from customers' perspectives. Future studies may use other methods to explore practitioners' views on the effectiveness of implementing chatbots, such as conducting interviews or focus groups with restaurant managers. Such managerial insights may also be very valuable when implementing chatbots to improve restaurant ordering experiences. In addition, as the adoption of chatbots in restaurants is still in its early stage, researchers should also conduct longitudinal studies to examine the impact of HRI on consumer experiences with continuously improving AI and robotic technologies.

Declaration of competing interest

None.

Note: black squares represent ordering methods; open circles represent food items.

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