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Determinants of customer purchase intention toward online food delivery services: The moderating role of usage frequency

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ABSTRACT

In this study, the determinants (i.e., social influence, effort expectancy, performance expectancy, trust, and food safety risk perception) affecting customers' purchase intention toward online food delivery services are explored based on the unified theory of acceptance and use of technology. The moderating effect of usage frequency between determinants and purchase intention is also examined to improve the understanding of the decision-making processes of frequent and non-frequent customers. Up to 392 responses are collected, and the results of this study indicate that performance expectancy, trust, and social influence positively affect customers' purchase intention toward online food delivery services. Positive relationships between determinants – social influence and performance expectancy, effort expectancy and performance expectancy – and the significant role of trust in effort expectancy and food safety risk perception are also identified. Furthermore, usage frequency significantly moderates the relationships between the determinants and purchase intention. Based on the findings, theoretical contributions and managerial implications for online food delivery service providers and restaurants are provided.

1. Introduction

Online food delivery services (OFDS) refer to food ordering and delivery systems that connect partner restaurants with customers through their websites or mobile applications (Ray et al., 2019). The OFDS market has steadily developed in the past few years, and the COVID-19 pandemic declared in March 2020 accelerated the rapid growth of its sales (EHL Insights, n.d.). Specifically, the number of U.S. OFDS users surged from more than 36 million in 2019 to approximately 46 million in 2020, and the number is expected to reach 54 million by 2023 (Statista, 2021).

Restaurants have benefited from OFDS by providing a new means of serving customers. However, as the service adds delivery to the traditional restaurant service process, OFDS creates potential risks to restaurant owners and customers in terms of temperature control during delivery, delivery drivers' hygiene, and even food tampering (Kim et al., 2008; Maimaiti et al., 2018). In addition, as customers using online/-mobile platforms often struggle with interface design, communication speed, and privacy and security of the service interfaces, including payment processors (Yeh & Li, 2009), OFDS customers are not free from these issues and express some degree of uncertainty about the service platforms (Kim et al., 2008). However, when customers trust the platform and gain confidence to engage in technology beyond the perceived risks associated with it (Hsiao et al., 2010; Kim et al., 2008), these risks can be minimized. In other words, e-commerce customers who trust a website or the platform are more likely to purchase products from the website because the risks associated with the website are offset (Kim et al., 2008). Moreover, building trust toward a service provider plays a pivotal role in enhancing customer satisfaction and loyalty to the entity, which ultimately contributes to its long-term profitability (Aslam et al., 2020; Assaker, O'Connor, & El-Haddad, 2020; Liébana-Cabanillas et al., 2016). Despite the important role of trust in the decision-making process of consumers, the effect of trust has been overlooked in the OFDS setting.

Several researchers have investigated OFDS purchase intention using various influential factors such as moral obligation in meal preparation (Roh & Park, 2019), technical aspects (Ray et al., 2019), consumer characteristics (Gunden et al., 2020), and customer perceptions of the COVID-19 pandemic (Hong et al., 2021). However, their studies are lacking in sufficient attention to the issue of how trust can minimize customers' risk perceptions, especially for delivered food or beverages (refer to Table 1). Moreover, as the focus of most of the existing studies is on the direct relationships between determinants and behavioral

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Table 1
Summary of the literature related to purchase intention toward OFDS.

References	Construct	Theory
Yeo et al. (2017)	Hedonic motivation Prior experience Time-saving orientation Price saving Convenience Usefulness Attitude Behavioral intention	Contingency Framework Model of IT continuance
Gunden et al. (2020)	Performance expectancy Congruity with self-image Habit Impulse buying tendency Mindfulness Usage intention	Unified Theory of Acceptance and Use of Technology (UTAUT2)
Ray et al. (2019)	Societal pressure Delivery experience Customer experience Ease of use Quality control Convenience Listing Search of restaurants Usage intention	Uses and Gratification Theory
Roh and Park (2019)	Convenience Compatibility Ease of use Usefulness Subjective norm Usage intention	Technology Acceptance Model
Belanche et al. (2020)	Attitude Subjective norm Perceived control Security App lifestyle compatibility Intention to use Word-of-mouth intention	Theory of Planned Behavior
Cai and Leung (2020)	Self-efficacy Construal mindset Regulatory focus Perceived benefits Perceived risk Risk propensity Purchase intention	Construal Level Theory Regulatory Focus Theory
Kaur et al. (2021)	Price value Health consciousness Food safety concerns Prestige value Affordances value Visibility Purchase intention	Theory of Consumption Values
Song et al. (2021)	Attention Interest Perceived usefulness Perceived ease of use Attitude Desire Behavioral intention	Technology Acceptance Model Attention, Interest, Desire, and Action model (AIDA)

intention to use OFDS, empirical evidence on the relationships between the determinants of OFDS has been scarce. Thus, understanding the complementary relationships among determinants is crucial because OFDS providers could improve their marketing and sales strategies in a more sophisticated manner. Furthermore, although previous studies have indicated that dining/usage/purchasing frequency significantly moderates the relationships between determinants and behavioral intention in various disciplines (Hernández et al., 2010; Liang & Zhang, 2011; Liébana-Cabanillas et al., 2016), no prior studies have examined the moderating effect of usage frequency in the OFDS context. The online food delivery market has gradually matured beyond the initial adoption stage with the increasing number of repeat customers; therefore, identifying the differences in the customers' purchase intention toward OFDS according to usage frequency and its significant determinants is necessary to enhance the understanding of the decision-making processes of frequent and non-frequent customers.

In light of this, the purpose of this study is to explore the determinants affecting customers' purchase intention toward OFDS by extending the unified theory of acceptance and use of technology (UTAUT) via the inclusion of the additional constructs of trust and food safety risk perception. Furthermore, this study seeks to verify the moderating effect of usage frequency between the determinants and the purchase intention toward OFDS.

2. Literature review

2.1. Unified theory of acceptance and use of technology

With the assumption that researchers are predisposed to select a favorite model or choose constructs across the models by neglecting contributions from other theoretical models to their study, Venkatesh et al. (2003) reviewed eight existing theoretical models that are widely adopted to explicate technology use and acceptance (e.g., theory of reasoned action, technology acceptance model, and theory of planned behavior). Venkatesh et al. (2003) consequently introduced an integrated model known as the unified theory of acceptance and use of technology (UTAUT). In the UTAUT, four main constructs (i.e., social influence, effort expectancy, performance expectancy, and facilitating conditions) are presented as significant factors of behavioral intention to use technology and actual usage. Social influence refers to "the extent to which consumers perceive those important others (e.g., family and friends) believe they should use a particular technology" (Venkatesh et al., 2012, p. 159). The second main construct of UTAUT is effort expectancy, defined as "the degree of ease associated with consumers' use of technology" (Venkatesh et al., 2012, p. 159). Performance expectancy pertains to "the degree to which using a technology will provide benefits to consumers in performing certain activities" (Venkatesh et al., 2012, p. 159). Although these three factors affect behavioral intentions, facilitating conditions, defined as "consumers' perceptions of the resources and support available to perform a behavior" (Venkatesh et al., 2012, p. 159), affect the actual usage.

The theory was originally developed to explore users' technology acceptance and usage in the organizational setting, but it has been successfully verified in numerous studies, particularly in the customer behavior context (Bhatiasevi, 2016; Ciftci et al., 2021; Lee et al., 2019; Okumus et al., 2018; Zhao & Bacao, 2020). However, Morosan and Jeong (2008) asserted that testing the UTAUT only with the original factors can mislead results in different contexts. Moreover, several studies revealed that amplifying the UTAUT with additional constructs, which are suggested from the validated theories, increases the predictive power of the model (Ciftci et al., 2021; King & He, 2006). Accordingly, researchers have widely extended and modified the UTAUT in various disciplines by adding numerous factors that fit in the context (Roh & Park, 2019). For instance, Okumus et al. (2018) incorporated personal innovativeness in the UTAUT to identify factors affecting the usage intention toward smartphone diet applications (apps) before ordering food at restaurants and found that performance expectancy, effort expectancy, social influence, and personal innovativeness significantly influenced usage intention. In the OFDS context, Zhao and Bacao (2020) extended the UTAUT by combining it with the expectancy confirmation model and task–technology fit model. Specifically, trust, perceived task–technology fit, and satisfaction were added to the original UTAUT, and the study results showed that performance expectancy, social influence, trust, and task–technology fit were significant predictors of the continuous intention to use OFDS. Following the perspective of previous research, this study attempts to include two additional constructs (i.e., trust and food safety risk perception) in the three main factors from UTAUT, namely performance expectancy, effort expectancy, and social influence, to improve the prediction of the determinants affecting the purchase intention toward OFDS. Facilitating conditions are omitted from the original model because several studies that adopted the UTAUT had identified the insignificant impact of facilitating conditions on technology usage behavior (e.g., Bhatiasevi, 2016; Lee et al., 2019; Okumus et al., 2018; Zhao & Bacao, 2020). The explanations of each construct included in the current study are detailed below.

2.2. Social influence

The perceptions of reference groups such as peers, family, and friends directly influence human behavior (Fishbein & Ajzen, 1977) because the belief that the relevant individuals expect the user to utilize a technology consequently creates a sense of belonging (Schepers & Wetzels, 2007). With the reasoning, the impact of social influence on effort expectancy has been empirically tested in several disciplines. For example, Shen et al. (2006) investigated the role of social influence in the online course delivery system and demonstrated that peers had no impact on recognizing the ease of use of the online course. By contrast, Choi and Chung (2012) proved that social influence positively affects effort expectancy in using social networking sites and implied that social pressure facilitates the discovery of effort expectancy. The current research similarly proposes that OFDS customers could be influenced in recognizing the beneficial and convenient aspects of OFDS by listening to the opinions or views of their reference groups and observing their use due to social pressure.

Previous studies also argued that social influence positively impacts the usefulness of the service, known as performance expectancy (Bonn et al., 2016; Choi & Chung, 2012; Shen et al., 2006). Specifically, when customers recognize usefulness, the internal belief is established in the process of incorporating the beliefs of reference groups (e.g., family, friends, colleagues) as part of an individual's belief system (Venkatesh & Davis, 2000). In other words, when people accept information from outsiders around them as their own opinions, the opinions facilitate the acknowledgement of the benefits of the service (Bonn et al., 2016). This is supported by the findings of Bonn et al. (2016) that customers recognize the usefulness of purchasing wine online when they observe that important people utilize online wine purchasing sites.

In contrast to dining in, OFDS requires customers to utilize technology such as mobile apps when placing an order; hence, it is important to understand customers' purchase intention, which predicts customers' actual purchasing behavior well (e.g., Ajzen et al., 2009; De Cannière et al., 2010; Fishbein & Ajzen, 2011) in relation to technology usage. Several studies on technology-related customer behavior revealed that social influence increases purchase intention, such as online flight ticket purchase (Escobar-Rodríguez & Carvajal-Trujillo, 2014), mobile banking (Bhatiasevi, 2016), and diet application (Okumus et al., 2018). For instance, Beldad and Hegner (2018) examined the factors affecting fitness application users' continuous usage intention and found social influence as a significant predictor. Multiple OFDS studies also indicated that customers are positively influenced by the opinions of their reference groups, which are strongly bonded, in utilizing OFDS (Al Amin et al., 2021; Lee et al., 2019; Roh & Park, 2019; Troise et al., 2020). Thus, the following hypotheses are developed in the present study:

H1. Social influence positively affects effort expectancy.

H2. Social influence positively affects performance expectancy.

H3. Social influence positively affects the customers' purchase intention toward OFDS.

2.3. Effort expectancy

In the original UTAUT, a direct association between effort expectancy and performance expectancy was not tested. However, in the technology acceptance model (TAM) proposed by Davis (1989), perceived ease of use (i.e., effort expectancy) was verified to positively influence usefulness (i.e., performance expectancy), and both concepts were deemed to be the same in terms of meaning. Consequently, the positive impact of effort expectancy on performance expectancy has been proved in various new technology adoption settings, such as fashion image search application (Hur et al., 2017) and mobile shopping application (Natarajan et al., 2017), and continuous usage behavior, including fitness application (Beldad & Hegner, 2018) and mobile learning (Al-Emran et al., 2020). These studies explicated that the higher effort expectancy customers have, the more positively customers predict that using the new technology would increase the productivity of their life. In the OFDS context, a recent study undertaken by Zhao and Bacao (2020) argued that ease of OFDS no longer had a meaningful impact on discovering the usefulness of the service in case of repeated usage; on the contrary, the majority of researchers who conducted OFDS-related studies found that once customers experience ease in using OFDS, they tend to consider the service useful (Roh & Park, 2019; Troise et al., 2020).

Furthermore, effort expectancy is a key predictor of user intention to adopt and continuously utilize online/mobile technology (e.g., Beldad & Hegner, 2018; Bhatiasevi, 2016; Okumus et al., 2018). Specifically, customers tend to be more loyal in using mobile banking service when the usage of such service requires less effort (Bhatiasevi, 2016). Beldad and Hegner (2018) similarly conclude that effort expectancy is a decisive factor in the continuous usage of a fitness application. However, as the use of smartphones and apps has reached maturity (Lee et al., 2019; Zhao & Bacao, 2020) and the interface of smartphone apps has stabilized due to the development of information and communication technologies over time (Lee et al., 2019), customers experience little difficulty in using new apps including OFDS as evidenced by recent studies in the OFDS literature; these studies have illustrated no significant association between effort expectancy and the continuous usage intention of OFDS (Lee et al., 2019; Zhao & Bacao, 2020). By contrast, multiple studies on the purchase intention toward OFDS have shown that effort expectancy positively affects purchase intention (Ray et al., 2019; Roh & Park, 2019; Troise et al., 2020). Taken together, although OFDS studies provide contradictory evidence regarding the impact of effort expectancy on purchase intention, much of the available literature indicates that customers have a higher purchase intention toward technology once they perceive that the usage is straightforward and clear. Therefore, the following hypotheses are formulated in this study:

H4. Effort expectancy positively affects performance expectancy.

H5. Effort expectancy positively affects customers' purchase intention toward OFDS.

2.4. Performance expectancy

Performance expectancy plays an essential role in using any service or product because customers' belief that a certain service or product will improve life or work productivity motivates their purchase (Lee et al., 2019). Particularly in technology-related service settings, the actual purchase is decided when the service is useful for completing certain activities (Morosan & DeFranco, 2016). Therefore, customers' perception of usability and utility of technology is regarded as a widely known factor of purchase intention toward technology-based self--services (Dabholkar & Bagozzi, 2002) such as a fitness application (Beldad & Hegner, 2018) and mobile banking (Bhatiasevi, 2016).

In the OFDS context, researchers have provided converging evidence for the relationship between performance expectancy and purchase intention (Hong et al., 2021; Jun et al., 2021; Lee et al., 2019; Zhao & Bacao, 2020). For instance, Hong et al. (2021) proved that performance expectancy is the strongest determinant of the purchase intention toward OFDS. Similarly, Zhao and Bacao (2020) revealed that OFDS customers intend to keep using the service due to its usability. Based on the findings, the following hypothesis is proposed in this study:

H6. Performance expectancy positively affects customers' purchase intention toward OFDS.

2.5. Trust

Customer trust refers to "a consumer's subjective belief that the selling party or entity will fulfill its transactional obligations as the consumer understands them" (Kim et al., 2008, p. 545). By applying the concept to the OFDS setting, customer trust can be expressed as the customers' belief that the OFDS will execute its transaction responsibilities about orders in a reliable manner. Numerous studies have highlighted the role of trust in online/mobile services in technology-related usage behaviors (Gefen, Karahanna, & Straub, 2003; Lai et al., 2013; Nguyen et al., 2019; Vatanasombut et al., 2008). Notably, trust in technologies and service providers helps recognize service convenience (Lai et al., 2013; McCloskey, 2006). Specifically, online shopping customers effortlessly find the ease of online shopping once they trust e-commerce (McCloskey, 2006). Similarly, trust in an online booking bed and breakfast website positively influences effort expectancy (Lai et al., 2013). Conversely, if users acknowledge that the service provider is unreliable, then they experience difficulty in finding its potential and instead focus more on its possible threats (Beldad & Hegner, 2018).

Trust in e-vendors also facilitates the perception of the services' benefits such as usability (Beldad & Hegner, 2018; Gao & Bai, 2014; Lai et al., 2013; McCloskey, 2006). For instance, McCloskey (2006) demonstrated that once online shopping consumers believe that their financial and personal data will be securely stored, they are more aware of the benefits of online shopping. In addition, Gao and Bai (2014) revealed that trust in the service provider plays a pivotal role in finding the usefulness of the Internet of Things technologies. Similarly, Beldad and Hegner (2018) established a strong positive relationship between trust in service providers and performance expectancy in the fitness application context.

Multiple studies have shown the significant impact of trust in online/mobile service providers on performance expectancy and effort expectancy in diverse disciplines; however, to the best of our knowledge, none of the existing OFDS studies have investigated the relationships. Due to the similar nature of OFDS with online/mobile service providers, in which transactions occur in online/mobile environment, this study follows the converging evidence of the previous research on customers' online/mobile service usage behavior and expects that if customers believe that OFDS offers a reliable service and fulfills its responsibility, then customers are more inclined to consider the service beneficial.

Furthermore, numerous studies on technology-related consumer behavior have verified the undeniable positive direct impact of trust on usage intention (Cho et al., 2019; Gefen et al., 2003; Lai et al., 2013; Nguyen et al., 2019; Vatanasombut et al., 2008; Zhao & Bacao, 2020). In particular, Nguyen et al. (2019) revealed that customers' trust in an online food shopping website positively influences their usage intention toward the website. In a similar vein, Vatanasombut et al. (2008) asserted that trust in an online banking service is a key motivator for the continuous use of online banking services. Existing OFDS studies also indicated that customers are more willing to use OFDS when they believe that the service would proceed correctly (Cho et al., 2019; Hong et al., 2021; Jun et al., 2021; Muangmee et al., 2021; Zhao & Bacao, 2020). Thus, the following hypotheses are developed in the present study:

H7. Trust positively affects effort expectancy.

H8. Trust positively affects performance expectancy.

H9. Trust positively affects customers' purchase intention toward OFDS.

2.6. Food safety risk perception

When consuming food, customers are not completely free from food safety hazards; additionally, how customers perceive the risk affects customer behavior (i.e., known as food safety risk perception) even more than the actual risk (Yost & Cheng, 2021). Nardi et al. (2020) define food safety risk perception as an "individual's perception of the presence of an attribute (safety) in food and the probability and severity of health consequences of its consumption" (p. 2). In the restaurant industry, food safety is a sensitive issue because food safety risk perception strongly influences the food-related buying decisions of customers (Dang & Tran, 2020; Ha et al., 2020; Ling, 2018; Shim & You, 2015). As Yeung and Morris (2001) underscore, customers' risk aversion becomes more intensified in food safety risk issues, and most customers severely consider the issues due to the vulnerability to their health. Supporting this view, Shim and You (2015) contended that consumers were less likely to purchase food products related to the 2008 melamine milk scandal and imported from the place where a nuclear plant accident had occurred once they perceived the potential food hazard of the products.

According to the trust-based consumer decision-making model developed by Kim et al. (2008), perceived risks are deterrents to the acceptance of a technology/service, and such risks can be reduced by cultivating the consumers' trust toward the technology/service (Kim et al., 2008). Specifically, trust in service providers provides consumers with the confidence that they willingly adopt a technology/service, although the perceived risks and uncertainties associated with the technology/service still exist (Hsiao et al., 2010; Kim et al., 2008). Consistent with this rationale, numerous studies have found that trust plays an essential role in settling the perceived risks that consumers could encounter in the purchase decision-making process (Chang & Chen, 2008; Hsiao et al., 2010; Kim et al., 2008; Marriott & Williams, 2018). For instance, Dang and Tran (2020) indicated that consumers who trust food distributors tend to perceive a low risk of purchasing meat from affected animals during an animal disease outbreak. By contrast, Ha et al. (2020) suggested that consumers who do not believe in food suppliers are more likely to feel that the foods are unsafe. Accordingly, this study proposes that customers with higher trust in OFDS might be less likely to perceive risks to food safety, such as food poisoning and contamination, which can occur during the delivery process.

Food safety-related problems can also cause foodborne illness, further harming customers' health (Arendt et al., 2013); in particular, a foodborne illness outbreak in a restaurant generates substantial costs, including lawsuits, fines, and medical expenses, resulting in the waste of a considerable portion of the restaurant's revenue (Arendt et al., 2013). Additionally, food delivery businesses cannot be free from food safety issues because the prepared foods from the kitchen are delivered not directly to customers but to their doorstep. According to a survey covering OFDS users, 36% experienced issues with freshness and food temperature (Freer, 2020). Customers also reported concerns about food hygiene and safety as a reason for not wanting to use OFDS (Opensurvey, 2020). As shown in this survey, the higher food safety risk customers recognize in using OFDS, a lower intention to use OFDS is evoked. Thus, the following hypotheses are formulated in the current study:

H10. Trust negatively affects food safety risk perception.

H11. Food safety risk perception negatively affects customers' purchase intention toward OFDS.

2.7. Moderating effect of usage frequency

Increased purchase experience forms an improved understanding of the consequences and benefits of the product or service (Hernández et al., 2010). As frequent customers update their beliefs and perceptions toward the service over time by accepting new information about the service (Boulding et al., 1993), usage frequency significantly influences consumer decision-making (Liébana-Cabanillas et al., 2016). Furthermore, loyal customers generate revenue gains for companies by expecting value from satisfactory service experiences (Umashankar et al., 2017); retaining frequent customers is therefore critical for business success (Alshurideh, 2019).

Researchers have proven the significant moderating effect of frequency on customer behavior in various settings (e.g., Hernández et al., 2010; Liang & Zhang, 2011; Liébana-Cabanillas et al., 2016; Tosun et al., 2015). Specifically in the context of restaurant customers, Liang and Zhang (2011) illustrated that frequent customers tend to have higher revisit intention toward a restaurant when the restaurant manages and interacts with customers well, but first-time customers' revisit intention is largely influenced by overall satisfaction with the dining experience. Similarly, Tosun et al. (2015) identified the different behaviors between frequent and non-frequent travelers regarding revisiting intention toward a destination. The study indicated that destination affective image played a vital role in frequent travelers' revisit intention, but it was insignificant to first-time travelers. Along with the findings supported by the existing literature, the present study hypothesizes that customers who have frequent experience may be more likely to understand the results and benefits obtained from OFDS; furthermore, the impact of their reference groups, trust in service, and food safety risk perception may differ from non-frequent customers. Therefore, the following hypotheses are proposed in this study:

H12a–e. Usage frequency moderates the relationships between the determinants and customers' purchase intention toward OFDS.

The proposed hypotheses in this study are depicted in Fig. 1.

3. Methodology

3.1. Measurements

A self-administered questionnaire was designed based on a thorough review of the literature (i.e., Castañeda et al., 2007; Hung et al., 2006; Lando et al., 2016; Xie et al., 2017; Yeo et al., 2017). The questionnaire was organized into two sections: measurement of the study constructs and socio-demographic information. Before beginning the survey, a screening question was provided to confirm that the respondents were over 18 years old, and a definition of OFDS was presented to have the same understanding of the concept. The first section of the survey comprised six constructs that were measured using a seven-point Likert scale (1 = strongly disagree to 7 = strongly agree), namely social influence, effort expectancy, performance expectancy, trust, food safety risk perception, and purchase intention toward OFDS. A list of items is presented in Table 3, and the items are slightly reworded to fit the OFDS context. The second section of the survey consisted of the socio-demographic information of the respondents, including gender, age, ethnicity, education, marital status, annual income, employment status, residency (urban, suburban, and rural), and OFDS usage frequency.

3.2. Data collection

U.S. consumers over 18 years were targeted in this study. To collect data, an online survey was conducted through Amazon Mechanical Turk (MTurk) in July 2020, which was amid the COVID-19 pandemic. Up to 462 responses were gathered during the data collection; however, in the process of data screening, 36 responses failed to answer three attention check questions, and six missing values and 27 extreme outliers were found. Furthermore, one response was omitted, which was completed faster than the minimum required response time of 2 s per item, as suggested by Huang et al. (2012) and DeSimone and Harms (2018). As a result, 392 responses were useable for further data analysis. Based on the recommendation of Nunnally (1967), a minimum sample size of 10 responses per variable (i.e., 10 × 17 variables = 170) is required to conduct the structural equation modeling (SEM). In addition, according to Kline (2015) and Weston and Gore (2006), a minimum sample size of 200 for any SEM analysis is recommended. Therefore, the sufficient sample size was confirmed in the current study.

To eliminate common method bias, procedural controls were utilized in the survey design process of this study. For example, at the beginning of the survey questionnaire, a clear definition of OFDS and the detailed instruction that all responses will remain anonymous were provided. Additionally, three attention check questions and reverse-worded measurement items were included (Baumgartner & Steenkamp, 2001), and the dependent and independent variables were separately placed on different survey pages to dissimulate their associations (Podsakoff et al., 2012). Moreover, Fuller et al. (2016) illuminated that common method bias levels can be discerned using Harman's single-factor test under

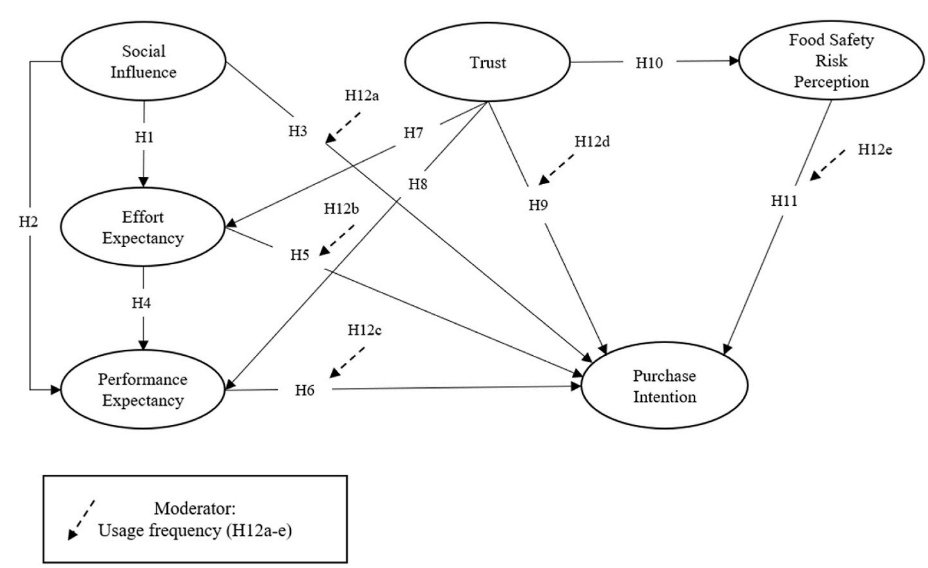

Fig. 1. Proposed conceptual framework.

Table 2
Profiles of respondents ($N = 392$).

Characteristics	Category	*n*	%
Gender	Male	220	56.1
	Female	172	43.9
Age	Less than 30 years	80	20.4
	30–39 years	150	38.0
	40–49 years	87	22.2
	50–59 years	46	11.7
	Over 59 years	29	7.4
Ethnic	Caucasian	286	73.0
	African American	36	9.2
	Hispanic	19	4.8
	Native American	4	1.0
	Asian	42	10.7
	Other	5	1.3
Education level	Less than high school	3	0.8
	High school graduate	28	7.1
	Some college	76	19.4
	College graduate	194	49.5
	Some graduate school	22	5.6
	Completed graduate	69	17.6
Marital status	Married	224	57.2
	Widowed	3	0.8
	Divorced	19	4.8
	Never married	146	37.2
Annual income	Under $10,000	11	2.8
	$10,000-$29,999	65	16.6
	$30,000-$49,999	91	23.2
	$50,000-$69,999	91	23.2
	$70,000-$89,999	55	14.0
	$90,000-$109,999	35	8.9
	Over $110,000	44	11.2
Employment status	Employed, full-time	249	63.5
	Employed, part-time	93	23.7
	Not employed	33	8.4
	Not employed, Student	8	2.0
	Retired	9	2.3
Residence	Urban	163	41.6
	Suburban	188	48.0
	Rural	41	10.5
Usage frequency	Once a month or less	138	35.2
	2-3 times a month	100	25.5
	1-2 times a week	90	23.0
	3-5 times a week	49	12.5
	More than 5 times a week	15	3.8

survey-based research conditions, so the test was performed after data collection as a statistical control. As a result, one factor explained 45% of the variance without rotation, indicating that no common method bias was found in this study.

3.3. Data analysis

In this study, a two-step approach suggested by Anderson and Gerbing (1988) was adopted using AMOS 26. A confirmatory factor analysis was initially conducted to check the reliability and validity of the measurement items; structural equation modeling was subsequently operated to test 12 hypotheses. Before the main data analysis, using SPSS 27, the normality of the data was confirmed by checking skewness (minimum: −1.029, maximum: 0.621) and kurtosis (minimum: −1.025, maximum: 1.239); the result demonstrated that all the values fell within the acceptable ranges of ±1 and ± 3, respectively (Hair et al., 2019).

Given that several studies indicated that the factors have significantly influenced the use of OFDS (Hong et al., 2021; Kaur et al., 2021), the current study controlled three demographic factors (i.e., age, gender, and household income) to confirm the pure impact of the predictors on the purchase intention toward OFDS. Age and household income were regrouped accordingly. Specifically, following Dhanapal et al. (2015) and Priporas et al.'s (2017) studies, age was divided into two groups, namely Generation Y/Z and Generation X/Baby Boomers. Additionally, household income comprised two categories: low (less than $69,999) and high (above $70,000).

4. Results

4.1. Sample profile

The socio-demographics of the respondents are shown in Table 2. Up to 56.1% of the respondents are male and 43.9% are female. Approximately 60% of the respondents were in their 20s and 30s, followed by respondents between 40 and 49 years old (22.2%), which aligns with the fact that the majority of food delivery app users are aged between 18 and 20, followed by 30- to 44-year-old app users (Zion & Hollmann, 2019). Most of the respondents are Caucasian (73.0%), and about half of the respondents had a college degree (49.5%). In terms of marital status, more than half of the respondents were married (57.2%). About a quarter of the respondents reported that their annual household income ranged from $30,000 to $49,999, and the same percentage of the respondents stated that their annual income was $50,000 to $69,999 (23.2%). Concerning employment status, two-thirds of the respondents (63.5%) were full-time employees, and about half of the respondents live in suburban areas (48.0%). More than one-third of respondents reported using OFDS once a month or less, followed by two to three times a month (25.5%).

4.2. Results of the confirmatory factor analysis

Confirmatory factor analysis (CFA) was performed to assess the measurement model by verifying the underlying structure of constructs. The scale's six-factor model was supported by CFA and reliability analysis. The measurement model exhibited acceptable fit statistics, with $\chi^2_{(104)} = 263.322$, $p < .001$, $\chi^2/df = 2.532$, CFI = 0.969, TLI = 0.959, RMSEA = 0.063 (90% CI: 0.053–0.072), and SRMR = 0.035. Tables 3 and 4 present the results of CFA and the construct validity of the measurement.

The internal consistency of the six constructs was acceptable, with composite reliability (CR) coefficients from 0.782 to 0.933 (Bagozzi & Yi, 1988). Convergent validity was established by examining both factor loadings and average variance extracted (AVE) for each construct. All the items were loaded significantly ($p < .001$) on their corresponding constructs, with the factor loadings ranging from 0.788 to 0.948. The AVEs ranged from 0.642 to 0.822, exceeding the recommended threshold. In addition, the AVEs were larger than the squared inter-construct correlations (Fornell & Larcker, 1981), and the AVE of each construct was greater than MSV (i.e., maximum shared variance). This result confirmed that the discriminant validity of the constructs was also acceptable. Furthermore, a more conservative approach called the heterotrait-monotrait (HTMT) ratio of correlations was adopted in the current study to verify the discriminant validity of constructs. Consequently, all the HTMT ratios exhibited lower than the recommended threshold of 0.85 (Henseler et al., 2015), implying that no validity issue was found in the present study.

4.3. Structural equation model and hypotheses test

After validating the measurement model, structural equation model (SEM) was conducted to assess the proposed structural model. The structural model was a good fit with the statistics ($\chi^2_{(158)} = 369.815$, $p < .001$, $\chi^2/\text{df} = 2.341$, CFI = 0.958, TLI = 0.950, RMSEA = 0.059 [90% CI: 0.051–0.066], SRMR = 0.056), suggesting that the structural model fit the data well. The results of the hypotheses are shown in Fig. 2. According to the results, no significant association between SI and EE was found ($\beta = 0.083$, $p = .244$, $f^2 = 0$). Thus, H1 was not supported. However, SI had a significant impact on PE ($\beta = 0.149$, $p < .05$, $f^2 = 0.02$) and PI ($\beta = 0.212$, $p < .001$, $f^2 = 0.04$), indicating H2 and H3 were supported with a small effect size according to the suggested thresholds of Cohen (2013). EE significantly influenced PE with a large effect size

Table 3
Measurement items and results of the confirmatory factor analysis.

Items	Standardized factor loadings	References
Social influence (SI)		Xie et al. (2017)
My peers/colleagues/friends think that I should use an OFDS for ordering meals.	.789	
People I know think that using an OFDS is a good idea.	.813	
Effort expectancy (EE)		Castañeda et al. (2007); Xie et al. (2017)
My interaction(s) with an OFDS is clear and understandable.	.788	
It is easy to become skillful at navigating through an OFDS.	.812	
Overall, an OFDS is easy for me to use.	.806	
Performance expectancy (PE)		Castañeda et al. (2007)
Using an OFDS is an efficient way to ordering my meals.	.841	
Using an OFDS makes my life easier.	.814	
Overall, using an OFDS is a useful way to order meals.	.899	
Trust (TR)		Hung et al. (2006)
I trust an OFDS.	.894	
I believe that an OFDS is trustworthy.	.841	
I trust an OFDS to do the job right.	.917	
Food safety risk perception (FSRP)		
It is likely for OFDS customers to get food poisoning because of the way food is delivered through an OFDS.	.904	Lando et al. (2016)
Contamination of food by being delivered by an OFDS is a serious food safety problem.	.866	
Food delivered by an OFDS is likely to have germs or other microorganisms that could make customers sick.	.948	
Purchase intention (PI)		Yeo et al. (2017)
I plan to use an OFDS in the future.	.916	
If possible, I will try to use an OFDS.	.880	
I will try to use an OFDS if necessary.	.842	

Note. $\chi^2_{(104)} = 263.322$, $p < .001$, $\chi^2/df = 2.532$, CFI = 0.969, TLI = 0.959, RMSEA = 0.063 (90% CI: 0.053–0.072), and SRMR = 0.035.

($\beta = 0.669$, $p < .001$, $f^2 = 0.53$), supporting H4; however, EE was not a significant predictor of PI ($\beta = 0.059$, $p = .450$, $f^2 = 0$), thereby indicating a failure to support H5. Instead, PE had a positive impact on PI ($\beta = 0.503$, $p < .001$, $f^2 = 0.12$), supporting H6 with a small approaching medium effect size. Moreover, TR had a significant impact on EE ($\beta = 0.624$, $p < .001$, $f^2 = 0.14$), PI ($\beta = 0.183$, $p < .01$, $f^2 = 0$) and FSRP ($\beta = -0.155$, $p < .01$, $f^2 = 0.02$), which supported H7, H9, and H10; the small or small approaching medium effect sizes were detected in those relationships. However, TR did not significantly influence PE ($\beta = 0.041$, $p = .572$, $f^2 = -0.01$), failing to support H8. In addition, FSRP had no significant association with PI ($\beta = 0.013$, $p = .714$, $f^2 = 0$); thus, H11 was not supported. In terms of control variables, the results showed that gender ($\beta = 0.032$, $p = .356$), age ($\beta = -0.022$, $p = .523$), and household income ($\beta = 0.001$, $p = .969$) had no significant impact on PI.

4.4. Moderating effect of usage frequency

In testing H12a–e, this study attempted to incorporate OFDS usage frequency as a moderator in the model to evaluate how usage frequency influences the strength of the relationships. Usage frequency was divided into two groups: non-frequent customers (n = 138, 35.2%) and frequent customers (n = 254, 64.8%). Given that customers are more likely to be familiar with mobile devices according to the usage experience (Ristola et al., 2005), customers using OFDS twice or more a month can be considered to have sufficient experience and knowledge of OFDS in understanding functions, processes, and benefits due to the repeated purchase experience (Han & Hyun, 2017). Thus, as shown in Table 2, customers who used OFDS more than 2–3 times a month (i.e., 2–3 times a month, 1–2 times a week, 3–5 times a week, and more than 5 times a week) belonged to frequent customers, whereas those who utilized OFDS once a month or less were considered non-frequent customers due to the relatively occasional purchase.

4.4.1. Measurement invariance test

Prior to testing the moderating effect of usage frequency, multi-group CFA was conducted to verify measurement invariance (*see* Table 5). The equal factor loadings model (i.e., factor loadings invariant) had an overall good fit to the data, and it did not significantly degrade the fit compared to the equal form model (e.g., loadings freely estimated), $\chi^2_{\text{diff}}(11) = 13.753$ ($p = .247$). This finding ensured the measurement invariance and showed evidence of comparable relationships to the latent constructs in low- and high-frequency groups.

4.4.2. Results of the moderating effect

The results of moderating effects are presented in Table 6. Chi-square differences with 1 *df* were used for comparing the constrained model with the unconstrained model for each of the five path coefficients (H12a–e). The results indicated that usage frequency significantly moderated the relationships between SI and PI (H12a: $\chi^2_{\text{diff}}(1) = 3.514$, $p < .10$), EE and PI (H12b: $\chi^2_{\text{diff}}(1) = 3.184$, $p < .10$), and TR and PI (H12d: $\chi^2_{\text{diff}}(1) = 4.867$, $p < .05$). However, usage frequency did not moderate the relationships between PE and PI (H12c) and FSRP and PI (H12e). More specifically, the relationships between SI and PI and EE and PI were positive for non-frequent customers, but non-significant relationships were found for frequent customers. Furthermore, the positive relationship between TR and PI was demonstrated for frequent customers, but no significant relationship for non-frequent customers was found. Fig. 3 depicts how each standardized path coefficient was differently loaded in both groups.

5. Discussion and conclusion

5.1. Key findings

With the increasing popularity of OFDS, this study attempted to examine factors driving PI toward OFDS by extending the UTAUT with the additional constructs of trust and food safety risk perception. This

Table 4
Validity analysis.

	CR	AVE	MSV	SI	EE	PE	TR	FSRP	PI
SI	.782	.642	.420	**.801**[a]					
EE	.844	.643	.591	.481[b]	**.802**				
PE	.888	.726	.591	.503	.770	**.852**			
TR	.915	.782	.458	.649	.683	.595	**.885**		
FSRP	.933	.822	.028	.099	.163	.155	.168	**.907**	
PI	.911	.774	.584	.618	.679	.770	.660	.082	**.880**

Note. Composite reliability (CR), Average variance extracted (AVE), Maximum shared variance (MSV), Social influence (SI), Effort expectancy (EE), Performance expectancy (PE), Trust (TR), Food safety risk perception (FSRP), Purchase intention (PI).

[a] Average variance extracted (values on the diagonal).

[b] Heterotrait-monotrait (HTMT) ratio of correlations.

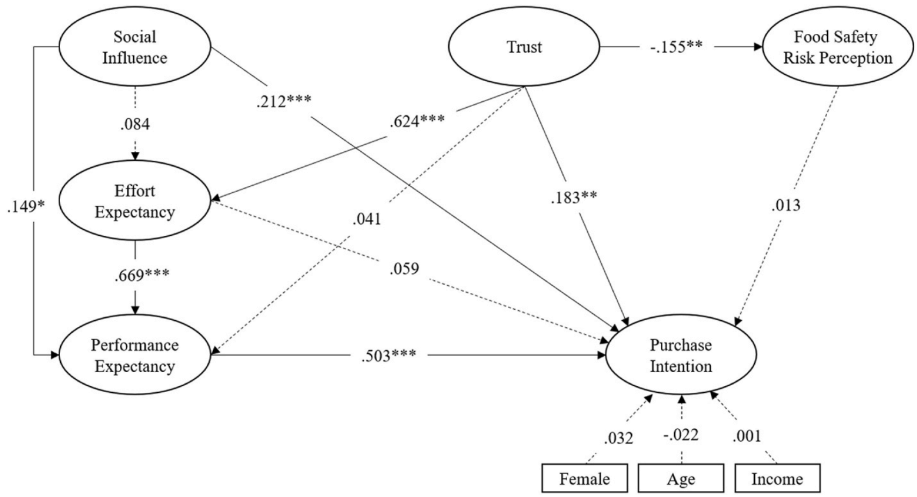

Fig. 2. Results of the structural equation modeling.

Table 5
Results of the measurement invariance test between non-frequent and frequent groups.

	χ^2	*df*	χ^2_{diff}	Δdf	RMSEA (90% CI)	SRMR	CFI	TLI
Measurement Invariance								
Equal Form	437.429***	208			.053 (.044–.060)	.045	.954	.940
Equal Factor Loadings	451.182***	219	13.753[a]	11	.052 (.045–.059)	.045	.954	.943

Note. ***$p < .001$, [a]Critical χ^2 value with 11 degrees of freedom at $p < .05$ is 19.675.

Table 6
Results of the moderating effect tests.

	χ^2	*df*	χ^2_{diff}	Δdf	RMSEA (90% CI)	SRMR	CFI	TLI	Hypotheses
Unconstrained Model	603.926	316			.048 (.042–.054)	.085	.943	.932	
Constrained Model									
SI → PI	607.440	317	3.514†	1	.048 (.043–.054)	.085	.943	.931	H12a: Supported
EE → PI	607.110	317	3.184†	1	.048 (.042–.054)	.085	.943	.931	H12b: Supported
PE → PI	605.972	317	2.046	1	.048 (.042–.054)	.085	.943	.932	H12c: [a]ns
TR → PI	608.793	317	4.867*	1	.049 (.043–.054)	.085	.943	.931	H12d: Supported
FSRP → PI	604.059	317	0.133	1	.048 (.042–.054)	.085	.943	.932	H12e: ns

Note. †$p < .10$, *$p < .05$, Critical χ^2 value with 1 degree of freedom at $p < .05$ is 3.84. [a]ns = not supported.

study revealed that out of three factors of SI, EE, and PE adopted from the UTAUT, SI and PE positively influenced PI. Specifically, PE was the strongest determinant of PI, indicating that customers need to perceive OFDS as a useful service that will benefit their lives. This finding supports previous studies that found the positive impact of PE on PI (Beldad & Hegner, 2018; Bhatiasevi, 2016; Hong et al., 2021; Jun et al., 2021; Lee et al., 2019; Roh & Park, 2019; Zhao & Bacao, 2020).

In the current study, SI also positively influenced PI; this finding shows that reference groups' opinions on OFDS play an important role in the use of OFDS, which aligns with earlier studies (e.g., Al Amin et al., 2021; Bhatiasevi, 2016; Escobar-Rodríguez & Carvajal-Trujillo, 2014; Lee et al., 2019; Okumus et al., 2018; Troise et al., 2020; Zhao & Bacao, 2020). Moreover, the result of the present study demonstrated the positive impact of SI on PE. This finding agrees with the findings of other researchers who proved that opinions from customers' reference groups facilitate the perception of the efficient and beneficial aspects of technology usage (e.g., Bonn et al., 2016; Choi & Chung, 2012; Shen et al., 2006). However, SI did not significantly affect EE, thereby indicating contradictory results compared with previous findings (e.g., Choi & Chung, 2012; Joe et al., 2022; Shen et al., 2006). This inconsistency may be explained by the fact that customers are familiar enough with online/mobile technology in this digital era. Thus, customers are hardly affected by other people's views or opinions regarding the ease of OFDS.

Additionally, the present study found that EE positively influenced PE, which corresponds with previous findings (e.g., Al-Emran et al., 2020; Beldad & Hegner, 2018; Hur et al., 2017; Natarajan et al., 2017; Roh & Park, 2019; Troise et al., 2020; Zhao & Bacao, 2020). These findings imply that customers who deem OFDS easy and comfortable are more likely to consider it useful and efficient and, in turn, are more predisposed to use OFDS. Furthermore, the result of this study proved that EE had no significant impact on PI. This result is inconsistent with previous literature findings, which demonstrate the positive impact of EE on PI (Beldad & Hegner, 2018; Bhatiasevi, 2016; Okumus et al., 2018). However, this result is in line with some studies on OFDS showing the insignificant relationship between two (e.g., Lee et al., 2019; Zhao & Bacao, 2020). A possible explanation for the result may be that the ease of the service does not attract customers to the service anymore because food delivery users in their 20s and 30s comprise a large portion of delivery app users who are familiar with various mobile apps (Hong et al., 2021; Lee et al., 2019).

The current study also examined the role of TR as an antecedent to FSRP and technology-related attributes (e.g., PE, EE). The results implied that TR positively affected EE but insignificantly influenced PE, although existing studies verified that customers' trust in a system/platform helps them to recognize the benefits and ease of mobile/online services (Beldad & Hegner, 2018; Lai et al., 2013; McCloskey, 2006).

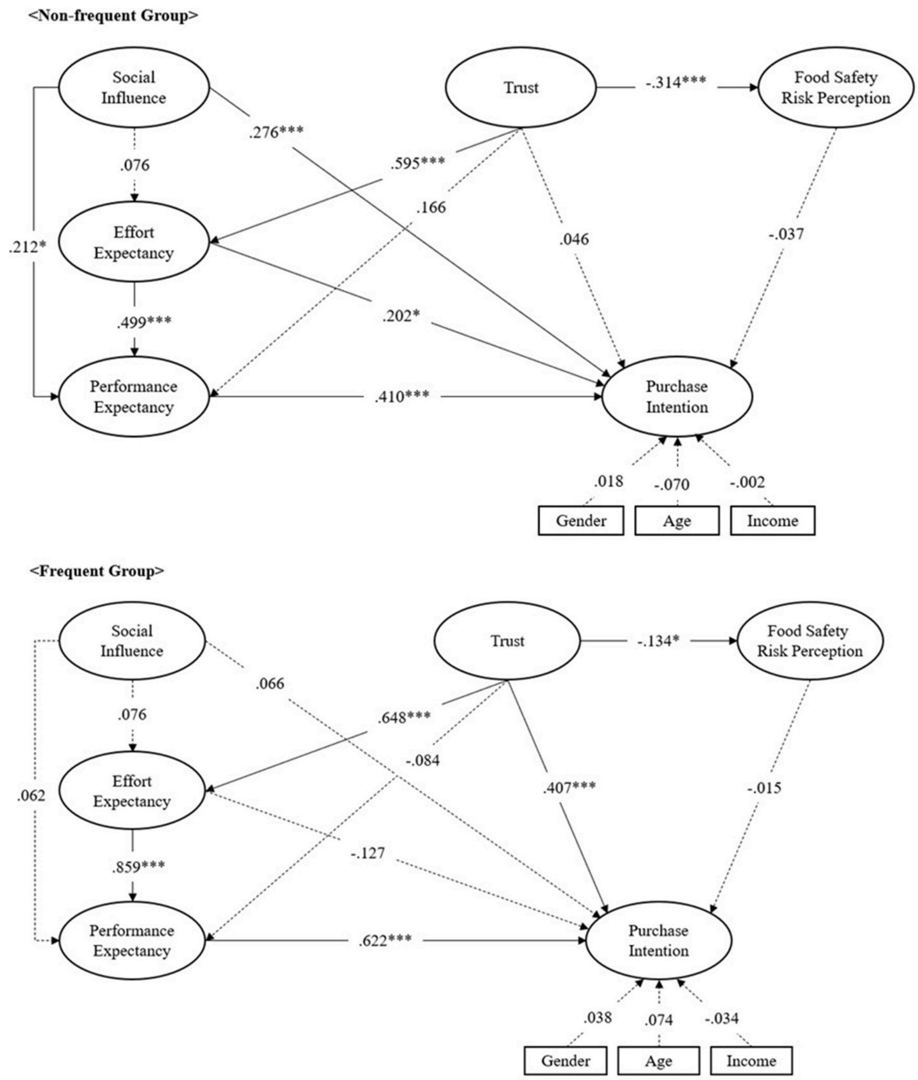

Fig. 3. Comparison of structural models between non-frequent and frequent groups.

This inconsistency may arise from the fact that customers who trust the OFDS could complete their transactions swiftly and effortlessly without doubt of the system, such that TR may be closely connected with the ease of the service rather than the efficiency of the service. In addition, TR had a significant negative impact on FSRP, which aligns with previous research indicating that trust in a system attenuates customers' perceived risks when deciding to make a purchase or not (Chang & Chen, 2008; Dang & Tran, 2020; Hsiao et al., 2010; Kim et al., 2008; Marriott & Williams, 2018). This finding suggests that trust in OFDS reduces the customers' concern about the hazard of the delivered foods and beverages.

In contrast to existing studies that found the negative impact of FSRP on PI (Ha et al., 2020; Ling, 2018; Shim & You, 2015), the present study revealed an insignificant relationship between FSRP and PI. This result may be explained by the fact that food delivery, especially on-premise delivery, has a long history in the U.S. and that U.S. customers probably do not consider OFDS differently in terms of food safety. Customers' previous experiences of OFDS in the current study might also contribute to the insignificant finding because approximately 65% of the respondents use OFDS more than twice a month. Considering a previous finding that showed Gen Y and Gen Z constituted 71% of survey respondents who reported they ordered delivery weekly (Beaton, 2021), frequent customers may not seriously consider food safety risks because they have confidence in the condition and freshness of the ordered foods or beverages due to their experience.

Moreover, this study investigated how usage frequency moderates the relationships between the determinant factors and PI and identified the significant moderating effects of usage frequency in the relationships between SI, EE, TR, and PI. Specifically, non-frequent customers are considerably affected by their reference groups' opinions and ease of OFDS, but those factors have no impact on the usage intention of frequent users. On the contrary, frequent users are more likely to use OFDS mainly due to their trust in OFDS, but trust is not a significant factor to non-frequent customers. This finding agrees with previous work identifying the significant moderating effects of dining/visit/usage frequency on the relationships between determinants and PI (Hernández et al., 2010; Liang & Zhang, 2011; Liébana-Cabanillas et al., 2016; Tosun et al., 2015). These findings imply that the key drivers for deciding online food delivery customer behavior differ according to their usage frequency.

5.2. Theoretical contributions

Several theoretical implications are highlighted in this study. Most importantly, the findings add to a growing body of literature on OFDS consumer behavior and influential determinants affecting the decision-making of users. Specifically, the relationship between technology-related attributes adopted from UTAUT is examined in this study, which no existing OFDS literature has attempted. The results indicate significant positive associations between EE and PE and SI and PE. The undeniable role of EE in PE is also established, although EE is not a significant determinant of purchase intention. This result illustrates that EE is still meaningful in OFDS customer decision-making, and the indirect effect can be expected due to the very strong positive impact between EE and PE.

Furthermore, this study is arguably the first work to identify the role of TR in the customer decision-making process in the OFDS context. By finding a significant relationship between, EE, FSRP, PI, and TR, this study fills the research gap regarding the role of trust as an antecedent to such factors.

This study also augments the limited knowledge on user perceptions of food safety and how it affects PI. Because of the delivery stage, customers might be concerned about food safety delivered through OFDS. However, this study provides empirical evidence that customers' concerns and risk perceptions of the delivered foods' safety do not affect PI.

Another insight that this study offers is the moderating effect of usage frequency on the relationship between the determinants and purchase intention in the OFDS context. The empirical finding that usage frequency significantly moderates the associations between SI, EE, TR, and PI adds to a substantial body of literature on online food delivery customer purchasing behavior, in which the role of usage frequency remains unanswered.

Finally, this study extends the knowledge of the use of technology in crisis situations such as pandemics and epidemics, as it entails the investigation of customer behavior using OFDS amid the COVID-19 pandemic.

5.3. Managerial implications

This study has noteworthy implications that industry professionals can utilize. PE, SI, and TR are highlighted in the findings as critical factors contributing to the purchase intention toward OFDS. Above all, considering that PE is the most influential factor of PI, OFDS companies should devote their efforts to enhancing the usefulness of the service. For instance, companies should connect with new restaurant businesses and expand their list of restaurants to enable various types of menus delivered. Additionally, although EE does not significantly affect PI, based on the finding that illustrates the positive impact of EE on PE, OFDS app developers can facilitate the use of OFDS as a means of increasing PE. Specifically, they need to regularly improve their interface for streamlined visuals and provide a seamless order process by storing customer payment information. A simple "re-order" function can also be implemented for repeat customers to order their favorite food or beverages with the least amount of effort, ultimately encouraging usability.

Moreover, the significant positive link between SI and PI suggests that OFDS marketers should focus on word-of-mouth marketing. According to Nielsen (2012), 92% of consumers believe a recommendation from friends and family more than other forms of advertising, and online reviews written by other customers are the second most trusted source of brand information and messaging. In this regard, OFDS marketers should promote user-generated content by making a unique hashtag of their service platforms and providing a gift or discount coupons to customers who share their experiences and reviews with pictures or videos on social media, which will increase visibility and stimulate new customers' curiosity by viewing the postings of their family or friends.

Furthermore, the study indicates that SI increases PE; hence, OFDS platforms should create ways to allow interactions among users. One approach is selling gift cards; some OFDS companies, including DoorDash, have recently begun selling digital/physical gift cards for the desired amount, which can be sent to the designated recipients (Hunter, 2020). During the COVID-19 pandemic, gift cards have become a new revenue stream for restaurants by immediately boosting sales; these digital/physical gift cards allow customers to treat delicious food to their lovers, friends, and family without meeting them in person (Voicu, 2021). As such, OFDS companies could also hold promotions to send a gift card that can be used on their platforms to order from their partnering restaurants, and the customers who send the gift card can also receive discount coupons or accumulated credit to use for their next purchase. This promotion is an effective means of advertising OFDS to new customers and guaranteeing loyal customers' next purchase.

The findings of this study showing that TR increases PI underscore that building trust with customers is necessary to stimulate customer purchase intention toward OFDS. Thus, OFDS companies need to provide reliable and accurate information on restaurant operations, including menu price, operation hours, delivery speed, nutrition information, and food ingredients. With this effort, OFDS companies can display prior customers' evaluations about the deliveries' accuracy and satisfaction with website/mobile applications. By revealing the evaluations, companies can trust other customers that the delivery will be similarly completed correctly. Moreover, restaurant owners should showcase their practices and efforts toward the COVID-19 guidelines via social media channels to gain the customers' trust. For instance, Wing Zone, an Atlanta-based restaurant chain, displays its safety procedures on its website and social media, noting that delivery drivers wear facial masks and gloves, and their restaurants sanitize insulated food delivery bags and seal packages for takeout/delivery (Littman, 2020). Such transparent efforts to protect customer safety are similarly required to build trust by engaging on social media, which ultimately improves customer perception toward the food safety risk of OFDS and increases customer loyalty.

Lastly, the moderating role of usage frequency is explained in this study. For OFDS marketers, the recommendation is to customize marketing strategies based on the usage frequency of customers. For frequent customers in particular, marketers could use trusted celebrity endorsement in advertising to attract them and gain their trust by citing reliable celebrities or influencers' recommendations. Moreover, as the significance of the impact of SI on PI to non-frequent customers is underscored in this study, personal endorsement is also an effective means of enhancing purchase intention through the most trusted people, such as friends and families (Ray, n.d.). To do so, a referral program can be implemented, in which frequent users can receive monetary benefits for inviting friends to utilize OFDS; at the same time, non-frequent users can also feel comfortable using this service via their reference group.

5.4. Limitations and future research

Despite its theoretical and practical contributions, this study has several limitations that must be acknowledged. In this study, purchase intention was measured as a proxy for actual purchasing behavior; thus, future research should consider measuring customers' actual purchase of OFDS if possible. Additionally, the data were collected during the COVID-19 pandemic in 2020, which could have affected the psychological aspects and lifestyles of the respondents and, in turn, their responses. Further research is needed to verify the findings of this study in a "new normal" and the post-pandemic era. Moreover, the focus of the present study was merely on the technology-related attributes (i.e., EE and PE), SI, and respondents' perception of trust and food safety risk as determinants affecting PI; hence, future research could include other plausible determinants (e.g., personality traits, hedonic motivation, and personal innovativeness) that might influence PI. Furthermore, among various techniques to detect common method bias, this study utilized Harman's single-factor test because it is the most widely used technique. Other techniques, such as the marker variable technique suggested by Bozionelos and Simmering (2022), might provide different results regarding common method bias. Finally, instead of focusing on a specific OFDS platform (e.g., Uber Eats, Grubhub, and DoorDash), this study considered OFDS as a whole third-party food delivery industry. As each individual has diverse preferences and attitudes toward different platforms, future studies can compare how they differ in determining the decision process.

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