

Understanding Food Delivery Mobile Application Technology Adoption: A UTAUT Model Integrating Perceived Fear of COVID-19

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Abstract

The COVID-19 pandemic has changed people's lifestyles and catalysed digital platform adoption, including within the context of the food delivery business. During the COVID-19 pandemic, food delivery mobile applications gained numerous new users, with the industry being one of the few domains to have leveraged the pandemic's outbreak. This study investigates the factors that have influenced the adoption of food delivery mobile application technology during the pandemic in Thailand. The research model was adopted from the Unified Theory of Acceptance and Use of Technology (UTAUT) model, integrating perceived fear of COVID-19. Empirical research was conducted using data from 223 food delivery mobile application users in Thailand, with Structural Equation Modelling used to validate the model and analyse the hypotheses. The results indicate that the intention to use food delivery applications was significantly influenced by social influence, performance expectancy, effort expectancy, and perceived fear. Facilitating conditions significantly impacted actual usage behaviour, with moderating results revealing a stronger influence on behaviour intention of perceived fear of COVID-19 among females than males and among younger respondents than older respondents. The variance explained by the modified UTAUT model for intention to adopt food delivery mobile application technology was found to be 59.4%. This research makes a significant contribution to the literature in terms of validating a theory-driven framework that emphasizes the factors which impact the adoption of food delivery mobile application technology in the context of the COVID-19 pandemic.

Keywords:

Food Delivery Mobile Applications;
The Unified Theory of Acceptance and Use of Technology;
COVID-19;
Thailand.

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1- Introduction

The COVID-19 pandemic has drastically changed people's lives, with one measurable impact being an upsurge in the adoption of food delivery mobile applications. Thailand's food delivery market is estimated to be worth over 1.1 billion USD, indicating a 17% growth rate for 2020 [1]. Although the industry had been growing at a rate of around 8% since 2017, the outbreak of COVID-19 catalyzed growth by largely preventing Thais dining at restaurants.

On March 26, 2020, the Thai government enforced a state of emergency, closing retail shopping centers in Bangkok and limiting restaurants to delivery and takeout. Lockdown, curfew, and social distancing policies were strictly implemented across the country, leading orders from customers using food delivery applications to increase by 100–300%. Meanwhile, the number of restaurants partnered with delivery services increased to at least three times the pre-COVID-19 numbers. The online food delivery industry has been one of the few business domains to leverage the

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pandemic, with O'Byrne (2020) observing substantial growth in the food delivery industry across the globe [2]. For example, the Chinese food delivery market was 20% bigger in January 2020 than it was a year earlier, and, in February 2020, up to 21% of American consumers ordered groceries online; in February 2019, this figure was only 18%. Meanwhile, the takeout and fast-food market in the UK recorded an 8.7% increase in sales, which includes food delivery. Thailand's food delivery business market is worth 1.07–1.14 million USD, 14% higher than the 2018 figure. According to a report from Kasikorn Research Center (2020) [3], app-based food delivery was expected to record a 17% growth for 2020, a result of people being hesitant to visit restaurants during the pandemic. Meanwhile, a March 2020 survey by the Electronic Transactions Development Agency [1] revealed that online delivery services were highly preferred (up to 85%) by Thai respondents during the pandemic, with 40% of online food delivery service users mentioning that their fear of COVID-19 was their main reason for adopting and using online food delivery services. Among respondents who used online food delivery services, 89% used applications such as GrabFood, LINEMAN, Food Panda, and Get Food.

The spread of COVID-19 has made food delivery applications a favored channel for online food ordering in countries where such approaches were not previously prevalent. Food delivery applications require less physical interaction, and users feel safer because they do not have to go to restaurants or interact with crowds of people. A survey of 2,500 US consumers by Cowen Inc. [4] revealed that 52% of respondents would avoid eating inside restaurants even after they reopen completely. In 2020, the pandemic boosted the total market value of the food delivery application industry by 200%, with revenue projected to reach \$14,670 million in 2024 [5]. Fears of COVID-19 infection catalyzed adoption, with perceived fear of COVID-19 recognized as "the push factor" motivating adoption intention. Previous studies have confirmed the relationship between health anxieties or fear and using health-related technologies, with Al-Marook et al. (2020) identifying a significant fear effect related to Google Meet adoption during the COVID-19 pandemic [6] and Wnuk et al. (2020) [7] revealing that adoption of COVID-19 tracking technologies was significantly predicted by users' perceptions of personal threat and loss of personal control.

Regarding the research method, the Unified Theory of Acceptance and Use of Technology (UTAUT) model is considered a well-developed and comprehensive model of technology acceptance, having been found to present superior explanatory power than other technology acceptance models; studies have observed up to 70% variance in explaining behavioral intention to use related technology systems [8, 9]. Recent studies have employed the UTAUT model to explain adoption intentions for technology systems and applications during the COVID-19 pandemic. For example, Walrave et al. (2020) extended the application of the UTAUT model to explain adoption intention for COVID-19 contact-tracing technology by incorporating innovativeness, app-related privacy concerns, and COVID-19-related stress constructs into the original UTAUT model [10]. The model features explanatory power (39%) to predict adoption intention of contact-tracing technology. Ezzaouia and Bulchand-Gidumal (2021) also predicted users' intentions to adopt COVID-19 contact-tracing apps, applying four additional specific drivers to the UTAUT model: perceived privacy, perceived value, safety, and accuracy [11]. Their results recognized that performance expectations most strongly influence the intention to use contact-tracing applications. Elsewhere, Lee et al. (2019) explored predictors of continuing to use food delivery applications by extending the UTAUT model to include four additional constructs: information quality, hedonic motivation, price value, and habit [12]. Their results demonstrated that habit most strongly impacted a continuous use intention, followed by performance expectations and social influence. However, to the best of our knowledge, adoption of food delivery applications has not been fully tested by academics or researchers, especially in the context of COVID-19, with few studies providing empirical evidence exploring factors influencing food delivery mobile application adoption during this period. Filling this research gap will provide insight for food delivery application stakeholders, enabling better comprehension of customer perceptions and behaviors and proficient crafting and execution of business strategies.

This research article is structured as follows. The second section reviews the relevant literature, as well as discussing the proposed research model and hypotheses developed. The third section comprises the research design, data collection process, and questionnaire development. The study's results are represented in section four. Finally, sections five and six present discussion and conclusions, including the study's limitations and avenues for future research.

2- Literature Review

2-1- Food Delivery Mobile Applications

Food delivery mobile applications can be defined as mobile applications downloaded by smartphone users who leverage them to access information about restaurants, browse food menus, order food items, and transfer payment without any physical contact with restaurant staff [13]. According to Euromonitor International [3], the proportion of online food orders compared to total food service sales grew almost threefold between 2014 and 2019, from 2.6% to 6.9%, a likely result of the emergence and successful implementation of online delivery platforms. These applications are widely used by customers to order their desired food from a wide range of menus and restaurants at a convenient time, receiving their food at their home or office without having to visit the restaurant physically. These food delivery mobile applications present comprehensive and up-to-date information about menu options and restaurants, as well as

enabling customers to track the progress of their order through multiple stages. These applications feature many advanced features that empower both restaurants and customers, reducing long wait times, offering proper communication and no-delay delivery, avoiding traffic jams, and resolving customer complaints [12].

There are two sorts of service providers involved in food delivery services [14]. First, restaurants, including fast-food chains such as KFC, Pizza Hut, Domino's Pizza, and McDonald's. The second category includes different restaurant intermediaries, which deliver food on behalf of partnered restaurants. In Thailand, these include LINEMAN, Lalamove, Food Panda, GET, GrabFood, and NOW.

In 2015, food applications were the second most downloaded mobile application type among Apple iOS users. Meanwhile, Sumagaysay (2020) has stated that approximately 60% of food catering customers have already subscribed to at least one food delivery mobile application [4], and CBRE Thailand (2020) recorded Thailand's major chain restaurants receiving 30% of food orders, with the remainder received by street food stalls and small and medium-sized enterprises (SMEs) [15]. In addition to Bangkok, food delivery businesses have expanded to other Thai cities, with GrabFood and LINEMAN, the country's two leading companies in the industry, even venturing into new and unexplored markets to increase their market share. For example, GrabFood started providing rideshare services in 20 cities across 18 provinces, aiming to expand its business to the tier-II cities that attract the most foreign tourists. Meanwhile, LINEMAN has claimed that its business network comprises 100,000 restaurants in Bangkok, Samut Prakan, and Nonthaburi, as well as 3,000 in Pattaya. It had previously stated that it aimed to cover 25% of Thailand by 2020 [15].

Knowledge about food delivery mobile application adoption in the COVID-19 context remains embryonic. However, there have been attempts to investigate factors affecting adoption of food delivery mobile applications before the COVID-19 crisis. For example, Pigatto et al. (2017) concluded that usability, content, and functionality exercised influence on customer adoption of food delivery mobile applications [16], and Yeo et al. (2017) [14], recognized that food delivery mobile applications are enjoyed by customers who feel that they are useful and make their day-to-day life easier, leading to a highly positive attitude towards the applications and continued use without hesitation. Additionally, the ability of food delivery mobile application to save customers time and money certainly influence attitudes and behavioral intentions.

2-2- The Unified Theory of Acceptance and Use of Technology Model

Venkatesh et al. (2003) proposed the UTAUT model to amalgamate different concepts and models, including Social Cognitive Theory, the De-composed Theory of Planned Behavior, the Theory of Reasoned Action, the Theory of Planning Behavior, the Technology Acceptance Model, the Innovation Diffusion Theory, the Model of PC Utilization, and the Motivational Model [8]. The UTAUT model considers adoption of information and communication technologies (ICT) according to four primary constructs: social influence (SI), performance expectancy (PE), effort expectancy (EE), and facilitating conditions (FC). While the constructions PE, EE, and SI impact behavior intention, FC influences the actual usage of information and communication technologies [17]. The authors also argued that these relationships are moderated by factors such as age, gender, age, experience, and voluntary usage.

The first construct, PE, denotes a person's perception of a product or service actually helping them or improving efficiency in their work or day-to-day life and make it efficient. Meanwhile, EE denotes an individual's anticipation of the technology's ease-of-use and usefulness of application for the intended purpose. Next, SI denotes the level of individual perception of the importance of using the new product, service, or system to integrate with peers. Finally, FC denotes the degree to which an individual believes that organizational and technical infrastructure exists to support the system's use. These constructs generate behavioral intention (BI), which describes the motivation to act or the lengths to which a person is ready to decide to adopt the technology [18, 19].

2-3- Conceptual Framework and Hypothesis Development

The current study's conceptual framework was based on the UTAUT model [8] and employed its four constructs of PE, EE, SI, and FC, with the first three used to determine usage intention and behavior and FC determining user behavior. According to Wnuk et al. (2020), the COVID-19 pandemic influences people's perceptions, with the degree of perceived fear of COVID-19 potentially driving and accelerating adoption of technologies that can minimize those fears [7]. Meanwhile, Al-Marooof (2020) assessed the impact of these COVID-19 factors on acceptance of Google Meet as an educational social platform within higher education institutions [6], finding that the perceived ease of use and the platform's perceived usefulness were significantly influenced by fear of education failure and fear of losing social relationships.

Based on these previous findings concerning technology adoption in the COVID-19 context, a perceived fear (PF) construct has been incorporated into the UTAUT model as a factor influencing behavioral intention to adopt food delivery application technology. Four moderating variables have been adapted to be consistent with the study context: gender, age, education level, and income. Our conceptual framework is presented in Figure 1.

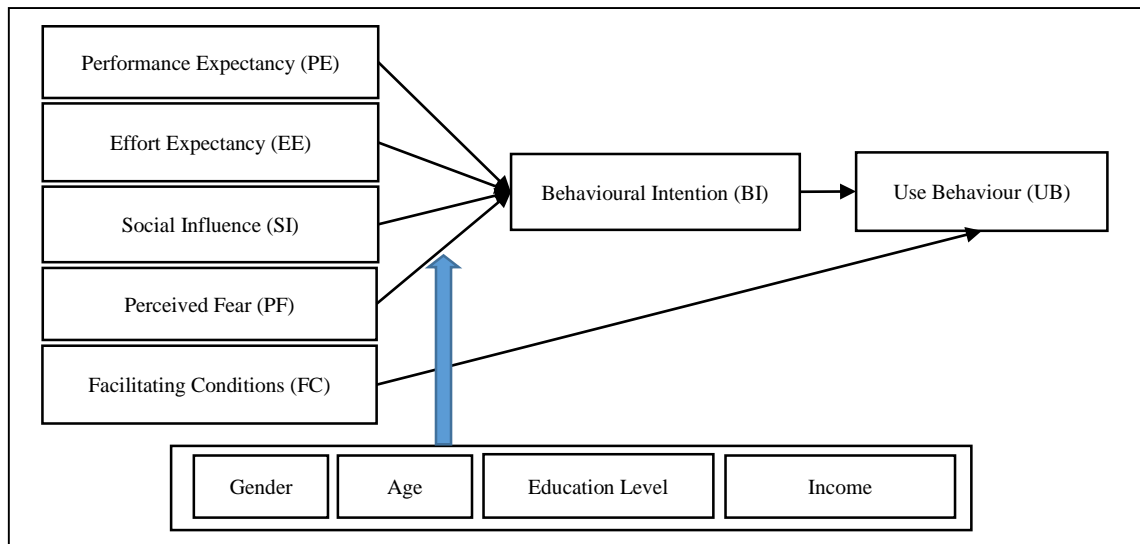


Figure 1. The study's conceptual framework.

The following hypotheses have been tested using this framework:

- H1: Performance expectancy significantly influences behavioral intention to use food delivery mobile applications;
- H2: Effort expectancy significantly influences behavioral intention to use food delivery mobile applications;
- H3: Social influence significantly influences behavioral intention to use food delivery mobile applications;
- H4: Perceived fear significantly influences behavioral intention to use food delivery mobile applications;
- H5: Facilitating conditions significantly influence use behavior;
- H6: Behavioral intention has a significantly positive effect on use behavior;
- H7: Demographic variables (gender, age, education level, and income) moderate the effect of perceived fear of COVID-19 on behavioral intention.

3- Research Methodology

3-1- Research Design and Data Collection

The purpose of this study is to investigate factors influencing food delivery mobile application adoption during the COVID-19 pandemic using the UTAUT model featuring the additional construct of PF. A quantitative research method was used, with Structural Equation Modeling (SEM) employed to check the validity of the hypotheses and to verify the conceptual framework. A convenience sampling technique was adopted, with an online questionnaire employed as the research instrument. Following data collection and screening, a total of 223 valid surveys were retained for analysis.

3-2- Questionnaire Development

The questionnaire comprised two parts. The first section concerned demographic and behavioral information. The second section consisted of measurement items based on the UTAUT model. Venkatesh et al. (2003), Palau-Saumell et al. (2019), and Zhao and Bacao (2020) were the primary sources for the UTAUT model measures that were modified and utilized in the current research [8, 17, 20]. Meanwhile, PF measurement items were adopted and modified from studies by Gerhold (2020) and Huynh (2020) [21, 22]. Responses to items used a 5-point Likert scale, with “strongly disagree” (or “never”) scored as 1 and “strongly agree” (or “always”) scored as 5. The five constructs describing independent variables—PE, EE, SI, FC, and PF—were each represented by four items. Dependent variables comprised two constructs—use behavior (UB) and behavioral intention (BI)—that were each represented by three items. Table 1 details each construct used by the questionnaire, corresponding to a total of 26 measurement items.

Table 1. Questionnaire constructs and variables.

Constructs	Items	Observed Variables
Performance Expectancy (PE)	PE1	I feel that food delivery mobile applications are useful for ordering and receiving delivery food during the COVID-19 pandemic.
	PE2	I feel that food delivery mobile applications are convenient for ordering and receiving delivery food during the COVID-19 pandemic.
	PE3	Using food delivery mobile applications improves the process of ordering and receiving delivery food.
	PE4	Using food delivery mobile applications has improved the efficiency of ordering and receiving delivery food during the COVID-19 pandemic.
Effort Expectancy (EE)	EE1	Learning how to use food delivery mobile applications is easy.
	EE2	It is easy to follow all the steps of food delivery mobile applications.
	EE3	It is easy to become skilful at using food delivery mobile applications.
	EE4	Interaction with food delivery mobile applications is clear and comprehensible.
Social Influence (SI)	SI1	People who are important to me (such as family members, close friends, and colleagues) recommend I use food delivery mobile applications during the COVID-19 pandemic.
	SI2	People who are important to me think food delivery mobile applications are beneficial during the COVID-19 pandemic.
	SI3	People who are important to me think it is a good idea to use food delivery mobile applications during the COVID-19 pandemic.
	SI4	People who are important to me support me using food delivery mobile applications.
Perceived Fear (PF)	PF1	The COVID-19 pandemic worries me.
	PF2	I am afraid of being infected by COVID-19.
	PF3	How likely do you think it is to get COVID-19 in general?
	PF4	Overall, to what extent do you worry about COVID-19?
Facilitating Conditions (FC)	FC1	I believe that I have the necessary smartphone to use food delivery mobile applications.
	FC2	I believe that I have the necessary knowledge to use food delivery mobile applications.
	FC3	I feel comfortable using food delivery mobile applications.
	FC4	I believe food delivery mobile applications are compatible with other technologies I use.
Behavioural Intention (BI)	BI1	I intend to use food delivery mobile applications in the future.
	BI2	I would use food delivery mobile applications to order foods.
	BI3	I plan to use food delivery mobile applications in the next month.
Use Behaviour (UB)	UB1	How much time do you spend using food delivery mobile applications when you are looking to order food?
	UB2	I have used food delivery mobile applications during the COVID-19 pandemic.
	UB3	I take advantage of food delivery mobile applications to order food.

4- Results and Discussion

4-1- Descriptive Statistic Results

The majority of respondents were females (51.6%) aged between 21 and 30 years with a marital status of single (58.9%), a bachelor's degree (49.6%), and a monthly salary below 664 USD (40.4%). Table 2 details respondent demographic details.

Table 2. Demographic statistics.

Item	Description	Sample	(%)
Gender	Male	108	48.4
	Female	115	51.6
Age	Less than 21	43	19.5
	21–30	76	34.2
	31–40	48	21.7
	41–50	32	14.3
	Above 50	23	10.3

Marital status	Single	131	58.9
	Married	87	39.2
	Others	4	1.9
Education	Below Bachelor's degree	34	15.1
	Bachelor's degree	111	49.6
	Master's degree or PhD	79	35.3
Monthly income (USD)	Below 664	90	40.4
	664–1,162	72	32.4
	1,162–1,826	38	17.2
	Above 1,826	22	10.0

Note: N = 223; missing data not shown and calculated in the table; 1 USD = 30.12 Baht

4-2- Measurement Model

For hypothesis testing, the authors used Confirmatory Factor Analysis, following Hair et al. (2010) [23], who indicated that construct validity could be defined as a threshold until the observed variables correspond to the latent variables, which are designed to be measured theoretically. Accordingly, the authors assessed Convergent and Discriminant validities, with the results confirming the number of items for each construct as follows: PE (4 items), EE (4 items), SI (4 items), PF (4 items), FC (4 items), BI (3 items), and UB (3 items). Cronbach's alpha was measured in the range of 0.848–0.904. Tables 3 and 4 summarize the results for the measurement model.

Table 3. Factor loadings, composite reliability (CR), average variance extracted (AVE), and Cronbach's alpha.

Construct	Item code	Item loadings	CR	AVE	Cronbach's alpha
Performance Expectancy (PE)	PE1	0.771	0.865	0.785	0.904
	PE2	0.794***			
	PE3	0.802***			
	PE4	0.772***			
Effort Expectancy (EE)	EE1	0.757***	0.838	0.751	0.883
	EE2	0.764***			
	EE3	0.742***			
	EE4	0.741***			
Social Influence (SI)	SI1	0.791	0.871	0.793	0.860
	SI2	0.785***			
	SI3	0.802***			
	SI4	0.793***			
Perceived Fear (PF)	PF1	0.835	0.837	0.868	0.852
	PF2	0.831***			
	PF3	0.886***			
	PF4	0.796***			
Facilitating Conditions (FC)	FC1	0.820	0.886	0.812	0.848
	FC2	0.839***			
	FC3	0.822***			
	FC4	0.768***			
Behavioral Intention (BI)	BI1	0.839	0.857	0.817	0.888
	BI2	0.817***			
	BI3	0.794***			
Use Behavior (UB)	UB1	0.803	0.842	0.800	0.895
	UB2	0.810***			
	UB3	0.786***			

Notes: PE1, EE1, SI1, FC1, and BI1 are fixed parameters; *p < 0.05; **p < 0.01; ***p < 0.001. Fit indices: Chi-square = 482.965; df = 278; CMIN/df = 1.737; GFI = 0.909; NFI = 0.934; TLI = 0.966; CFI = 0.971; RMSEA = 0.044

Table 4. Discriminant validity.

	PE	EE	SI	PF	FC	BI	UB
PE	0.886						
EE	0.408	0.867					
SI	0.399	0.435	0.890				
PF	0.358	0.291	0.241	0.915			
FC	0.533	0.312	0.240	0.493	0.901		
BI	0.578	0.334	0.371	0.318	0.478	0.904	
UB	0.255	0.388	0.224	0.527	0.373	0.259	0.894

Notes: The diagonal elements in bold in the table denote the AVE square root for every construct used in the study. Non-diagonal elements denote correlations between constructs

As Table 3 shows, analysis of measurements with seven constructs attains a satisfactory model fit (Chi-square = 482.965; df = 278; CMIN/df = 1.737; GFI = 0.909; NFI = 0.934; TLI = 0.966; CFI = 0.971; RMSEA = 0.044). Convergent validity is indicated by several indicators, including item loading (standardized estimates), average variance extracted (AVE), and composite reliability (CR). These measures attained the values suggested by Hair et al. (2010) [23]: i.e., AVE>0.5 and CR>0.7. This indicates acceptance of convergent validity. Table 5 indicates that the discriminant validity test has been provided. The study attained discriminant validity because each construct's AVE square root was higher than the respective inter-construct correlation estimates.

4-3- Structural Model and Hypotheses Testing

Upon evaluating the measurement model, the structural model was developed. Figure 2 demonstrates outcomes for the path model, demonstrating an adequate model fit to the data.

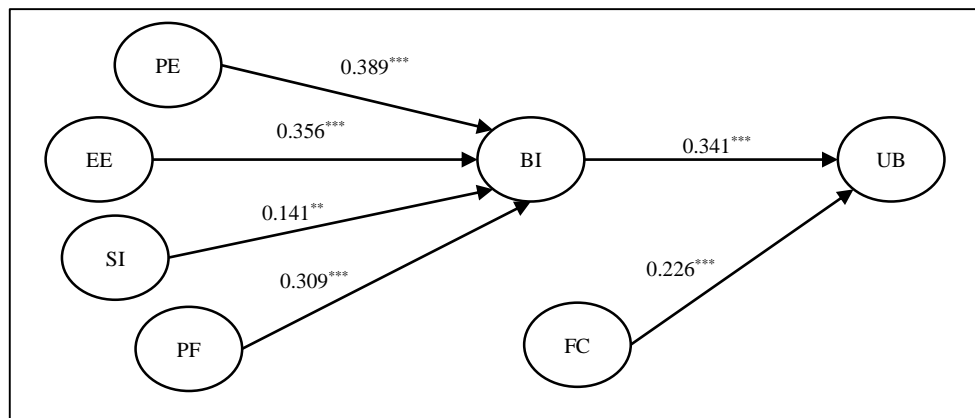


Figure 2. SEM results. Notes: *p < 0.05; **p < 0.01; ***p < 0.001. Fit indices: Chi-square = 545.112; df = 283; CMIN/df = 1.926; GFI = 0.900; NFI = 0.926; TLI = 0.957; CFI = 0.963; RMSEA = 0.049.

Table 5. Structural parameter estimates.

Hypotheses	Relationship	Estimate (b)	Result
H1	PE → BI	0.389***	Supported
H2	EE → BI	0.356***	Supported
H3	SI → BI	0.141**	Supported
H4	PF → BI	0.309***	Supported
H5	FC → UB	0.226***	Supported
H6	BI → UB	0.341***	Supported

Notes: R2 (Behavioral Intention) = 0.503; R2 (Use Behavior) = 0.389; *p < 0.05; **p < 0.01; ***p < 0.001

The hypothesized path model outcomes indicate an adequate model that was fit to the data (Chi-square = 545.112; df = 283; CMIN/df = 1.926; GFI = 0.900; NFI = 0.926; TLI = 0.957; CFI = 0.963; RMSEA = 0.049). For latent variables, the residual variances for BI and UB were 0.50 and 0.39. Table 6 shows the results for hypothesis testing, which indicate significance for the six hypotheses.

Specifically, the outcomes supported the hypotheses concerning the relationship between PE and BI (H1: b = 0.389, t-value = 4.527, sig < 0.001), between EE and BI (H2: b = 0.356, t-value = 4.338, sig < 0.001), between SI and BI (H3: b = 0.141, t-value = 2.542, sig < 0.001), and between PF and BI (H4: b = 0.309, t-value = 4.061, sig < 0.001). Meanwhile,

supporting H5, FC were observed to positively impact UB (H5: $b = 0.226$, $t\text{-value} = 3.562$, $\text{sig} < 0.001$) and, supporting H6, BI was observed to positively impact UB (H6: $b = 0.341$, $t\text{-value} = 4.234$, $\text{sig} < 0.001$).

To test H7, multi-group moderation tests were conducted to explore the variation effect of PF on the dependent variable BI. The authors first transformed three moderating variables (age, education level, income) into dichotomous variables (older vs. younger age group, high vs. low education level, high vs. low income).

The research developed critical ratios to assess the moderation hypotheses. These ratios were developed for differences in regression weights between groups of demographic variables using Analysis of Moment Structures (AMOS), a stats package provided by Gaskin and Lim (2018) for testing multi-group moderation effects using regression weights and critical ratios for different parameters [24]. This study's authors assessed the relevant models separately for the dichotomous groups and conducted a comparison with the respective regression weights and critical ratios for group differences (see Table 6).

Table 6. Pathwise moderation effect: Group differences.

Group Differences		Structural path and direction BI \leftarrow PF			Result
		Estimate	P	z-score	
Gender	Male	0.235	0.000	3.472***	Supported
	Female	0.387	0.000		
Age	Younger (less than or equal to 30 years old)	0.392	0.000	4.285***	Supported
	Older (above 30 years old)	0.244	0.000		
Education	Low (bachelor's degree or lower)	0.318	0.000	1.894	Not Supported
	High (Master's degree or Ph.D.)	0.296	0.000		
Income	Low (less than or equal 1,162 USD)	0.301	0.000	1.733	Not Supported
	High (more than 1,162 USD)	0.325	0.000		

Notes: *** p-value < 0.01; ** p-value < 0.05; * p-value < 0.10

The results shown in Table 6 suggest a significant and positive impact of PF on BI for both male ($\beta=0.235$, $p < 0.001$) and female ($\beta=0.387$, $p < 0.001$) participants. The results demonstrate a strong PF effect upon BI for females compared to males ($Z\text{-score}=3.472^{***}$). Regarding age, PF significantly and positively impacted BI among younger ($\beta=0.392$, $p < 0.01$) and older ($\beta=0.244$, $p < 0.01$) age groups. The results showcase a strong effect of PF was experienced upon BI by younger than the older group ($Z\text{-score}=4.285^{***}$). However, as a result of moderating effect testing (also shown in Table 6), the authors observed no statistically significant difference between the highly educated group and the less educated group ($Z\text{ score} = 1.894$) or between the high- and low-income groups ($Z\text{ score} = 1.733$). Based on the moderation effect results, H7 is supported.

5- Conclusions

Previous studies have confirmed that the COVID-19 pandemic accelerated digital adoption in numerous industries, including education [25], medical [26], and corporate [6] institutions. The McKinsey Global Survey [27] indicated that corporations had increased digitization of their processes, especially customer and supply-chain interactions and internal operations, over the past 3-4 years. This situation has also been observed in the food delivery industry, with a forecast by Deliveroo [28] indicating that COVID-19 had increased the pace of consumer adoption of such delivery services by 2-3 years. This paper is amongst the first attempts to explain adoption of food delivery mobile applications during the COVID-19 pandemic, contributing to the existing literature on food delivery mobile applications by integrating the UTAUT model with PF of COVID-19, with results highlighting the need to integrate PF into the original UTAUT model to expand understanding of the main determinants of food delivery mobile application adoption intention and usage.

The results suggest that constructs such as PE, EE, SI, and PF have strongly impacted BI to adopt food delivery mobile application technology during the COVID-19 pandemic. A significant positive impact of FC upon UB was also observed. The research model recognized about 59.4% variance in BI, which was influenced by four constructs, including PE, EE, SI, and PF. The moderation analysis results revealed that the impact of PF of COVID-19 on BI was stronger among females than males and stronger among younger respondents than older respondents. These results have both theoretical and practical implications. First, this study is among the first empirical studies that have attempted to integrate the notion of fear into the UTAUT model to analyze the impact of COVID-19 on adoption of food delivery mobile application technology, contributing to the literature on UTAUT by providing an addition to its existing three constructs affecting individual BI.

That is, this study's findings empirically demonstrate that, during an unprecedented situation such as a global pandemic, integrating other constructs into existing technology acceptance models, such as the UTAUT model, may provide more fruitful results and better explain adoption of technology. The study also has practical and managerial implications for policymakers and practitioners. First, ordering food items through an online food delivery application is a very effective way for citizens to avoid crowded areas, suggesting that food delivery businesses should emphasize the advantage of adopting and using food delivery applications as a mechanism for lowering the possibility of COVID-19 infection. Second, food delivery services should promote and offer contactless delivery, meaning that those ordering food can get it delivered without interacting face-to-face with their delivery driver. Customers should be able to request delivery drivers drop food off in the lobby of their building or outside their house to mitigate the risk of exposure to COVID-19.

5-1-Limitations and Future Research

Although this study aimed to explore BI and UB regarding food delivery mobile applications in the COVID-19 context, empirical data collection only took place in Thailand. Future research should expand the boundaries to investigate other countries—where there are differences in terms of culture, values, and beliefs—to verify the validity of this study's model. Furthermore, being a cross-sectional study, this research was completed within a short period of time. The perceptions of the customers who use food delivery mobile applications in terms of PE, EE, SI, and PF can change at any time. Accordingly, future research studies should employ a longitudinal design, analyzing the time sequence in the relationships between constructs. Finally, a self-reported questionnaire was used as this study's research tool. This means respondents may not answer truthfully or may provide invalid answers. In the future, a mixed-methods approach could be used to provide deeper insight into food delivery mobile application technology adoption and usage.

6- Declarations

6-1-Author Contributions

W.P. conceptualized and participated study design, coordinated data collection, carried out the initial analyses, drafted the initial manuscript, and read and approved the manuscript. S.T. participated in study design, guided the methodology coordinated and supervised data collection and analyses, reviewed and edited manuscript. Both authors read and approved the manuscript as submitted and agree to be accountable for all aspects of the work.

6-2-Data Availability Statement

The datasets generated during and/or analyzed during the current study are not publicly available due to IRB stipulations but are available from the corresponding author on reasonable request.

6-3-Funding

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6-4-Conflicts of Interest

The authors declare that there is no conflict of interests regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, and redundancies have been completely observed by the authors.

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