

ATTITUDE AND INTENTION TO USE FOOD DELIVERY PLATFORMS: EVIDENCE FROM SECOND-YEAR STUDENTS AT A VOCATIONAL COLLEGE IN LIAONING, CHINA

Zhang Yuyang

PhD. TEM, Graduate School of Business and Advanced Technology Management,
Assumption University, Thailand.

E-mail: 115602411@qq.com

Received: 12 March 2026

Revised: 17 April 2026

Accepted: 23 April 2023

Abstract

This study examines the factors influencing sophomore students' attitudes toward continuing to use food delivery service systems (FDSS) in Liaoning, China. It extends technology adoption research by focusing on the post-adoption stage, where accumulated service experiences shape user evaluations. A quantitative research design was applied. Data were collected through an online questionnaire from 500 sophomore students enrolled in colleges in Liaoning Province using non-probability sampling. Confirmatory factor analysis assessed reliability and validity, followed by structural equation modeling to examine the relationships among Compatibility, Emotion, Performance Expectancy, Perceived Ease of Use, Perceived Usefulness, Attitude, and Intention to Use. The results show that all hypothesized relationships were significant ($p < 0.001$). Compatibility and Emotion were the strongest predictors of Attitude, followed by Perceived Usefulness, while Perceived Ease of Use and Performance Expectancy showed smaller but significant effects. Attitude strongly influenced Intention to Use. The findings suggest that continued FDSS use among experienced students is mainly driven by lifestyle compatibility and positive emotional experiences rather than functional attributes, highlighting the importance of experiential factors in post-adoption digital service usage.

Keywords: Attitude, Intention to Use, Food Delivery Services, Technology Acceptance

Introduction

The digitalization of consumption has transformed food delivery services, particularly through the integration of mobile applications, artificial intelligence, and real-time logistics. Modern food delivery service systems (FDSS) extend far beyond simple telephone ordering. They now provide personalized recommendations, instant payment, and service optimization based on big data. These developments have changed not only how food is delivered but also how consumers evaluate and interact with service platforms. In China, the food delivery market has experienced rapid growth, with approximately 545 million users, reflecting its significant economic and social impact (China Internet Network Information Center, 2023). Despite this expansion, maintaining user engagement and long-term retention remains a key challenge for platform providers.

College students represent an important segment of the food delivery market. Their consumption behavior is influenced by academic pressure, limited time, urban living conditions, and familiarity with digital technologies. As a result, food delivery platforms are often integrated into students' daily routines. However, frequent use does not necessarily indicate stable acceptance. Many platforms face challenges in retaining student users beyond initial adoption, as continued usage depends on sustained satisfaction and service experience. Students' intention to use FDSS may depend on perceived efficiency, emotional satisfaction, and compatibility with personal lifestyles.

Existing research based on the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) highlights the importance of perceived usefulness and perceived ease of use in predicting behavioral intention (Davis, 1989; Venkatesh et al., 2003). Recent studies also suggest that emotional factors and compatibility influence users' attitudes toward digital platforms (Ham et al., 2024). However, prior studies often focus on initial adoption and examine these factors independently. Limited research explains how cognitive, emotional, and compatibility factors interact in shaping post-adoption attitudes among experienced users, particularly second-year vocational students.

Food delivery platform development also varies across regions (Palas et al., 2022). Liaoning Province provides a suitable context, especially among second-year vocational students who have accumulated usage experience. This focus allows the study to extend TAM and UTAUT into the post-adoption stage and provide a more experience-based perspective.

The objectives of this study are: (1) to examine the effects of cognitive, emotional, and compatibility factors on students' attitudes toward FDSS, (2) to analyze the influence of attitude on intention to use, and (3) to extend technology acceptance models in a post-adoption context.

The research questions are: RQ1: What factors influence students' attitudes toward FDSS? RQ2: How does attitude affect intention to use? RQ3: How do cognitive, emotional, and compatibility factors interact in shaping post-adoption behavior?

Literature Review

1. Compatibility (COM)

Compatibility refers to how well a technology fits users' existing habits, needs, and lifestyles. In mobile food delivery services, it reflects how smoothly the service integrates into students' daily routines. When a system aligns with familiar behaviors such as simple ordering processes and convenient payment methods, users are more likely to evaluate it positively (Ayo et al., 2016). For second-year vocational college students, compatibility reflects how well the system supports their academic schedules and daily activities.

Technological integration also plays an important role. Food delivery service systems (FDSS) that connect with commonly used digital applications can enhance convenience and overall user experience (Labrecque et al., 2017). According to diffusion of innovations theory, alignment with users' values, experiences, and needs supports technology acceptance (Rogers, 1995). Therefore, when FDSS features match students' lifestyles and digital habits, they are more likely to develop favorable attitudes toward the platform (Chin, 2014; Püschel et al., 2010).

H1: Compatibility has a significant influence on attitude.

2. Emotion (EM)

Emotion refers to a multidimensional affective response that reflects how individuals interpret and evaluate their experiences (Kleinginna & Kleinginna, 1981). In food delivery services, students' emotions are shaped by how well the service experience meets their expectations. Positive emotions arise when performance meets expectations, while dissatisfaction occurs when expected and actual service quality mismatch.

Previous research indicates that emotional responses are closely linked to cognitive evaluation. Users' feelings toward a service depend on how they perceive the outcomes of their consumption experience (Bagozzi et al., 1999). In technology-based services, emotions can influence users' decisions to continue using a service (Martensen & Grønholdt, 2016). Engagement with mobile applications may also strengthen emotional attachment and support acceptance of digital platforms (Riedel et al., 2022). In addition, anticipatory emotions, shaped by prior experience, can further influence user attitudes (Bettiga & Lamberti, 2018). Recent research on mobile food delivery applications also confirms that emotional satisfaction significantly influences continued usage behavior (Munday et al., 2024). Therefore, emotional responses toward food delivery service systems are likely to influence students' attitudes toward the platform.

H2: Emotion significantly influences attitude.

3. Performance Expectancy (PE)

Performance expectancy refers to the degree to which users believe that a system improves task performance and efficiency (Venkatesh et al., 2003). For sophomore students, this perception is shaped by prior experience rather than initial expectations. Their evaluation develops through repeated interactions with food delivery service systems (FDSS) and comparisons with other digital platforms or traditional dining options (Allah Pitchay et al., 2022).

In FDSS, performance expectancy reflects whether the system saves time, supports meal planning, and provides reliable access to preferred food choices, especially during busy academic schedules (Yang, 2010). Consistent service performance strengthens users' perceptions, while delays or service problems may reduce their confidence in the platform (Bhattacharjee & Premkumar, 2004).

Research also indicates that performance expectancy is related to perceived relative advantage, which influences users' preference for digital services over traditional alternatives (Baca & Zhushi, 2025; Moore & Benbasat, 1991). Therefore, higher performance expectancy is likely to lead to more favorable attitudes toward FDSS.

H3: Performance Expectancy has a significant influence on attitude.

4. Perceived Ease of Use (PEOU)

Perceived ease of use refers to the degree to which users believe that operating a system requires minimal effort (Davis, 1989). For sophomore students, this perception focuses less on learning and more on whether routine activities remain smooth. These activities include searching for restaurants, modifying orders, checking discounts, and completing payment without difficulty (Gefen & Straub, 2000).

Students who are familiar with digital platforms may be sensitive to minor usability issues. Problems such as unclear interface changes, location errors, or complicated checkout procedures may negatively affect their evaluation of the system (Lee et al., 2006). Perceived ease of use therefore remains important beyond the initial adoption stage because it determines how easily users can benefit from system functions (Davis et al., 1989; Venkatesh & Davis, 2000). Recent studies on digital platform adoption continue to show that ease of use remains a key determinant of user acceptance, even in evolving digital service environments (Al-Qudah et al., 2024). When the platform operates smoothly and requires little effort, users are more likely to develop favorable attitudes toward the service (King & He, 2006).

H4: Perceived Ease of Use has a significant influence on attitude.

5. Perceived Usefulness (PU)

Perceived usefulness refers to the degree to which users believe that a system improves their performance and provides beneficial outcomes (Davis, 1989). For sophomore students, this perception is shaped by experience with the system. They evaluate whether food delivery service systems (FDSS) save time, increase convenience, and help manage daily schedules and limited dining options (Venkatesh et al., 2003).

Prior studies indicate that perceived usefulness is a key factor influencing users' attitudes because it reflects the practical value obtained from using the system (Gefen et al., 2003; Schierz et al., 2010). It is also closely related to usability. When a system is easy to use, users can access its benefits more efficiently, which strengthens their perception of usefulness over time (Bhattacharjee & Premkumar, 2004).

In digital services, perceived usefulness reflects users' belief that the system helps them perform tasks more effectively (Wang et al., 2017). Therefore, higher perceived usefulness is likely to lead to more favorable attitudes toward FDSS and stronger intention to use the platform (Venkatesh & Davis, 2000).

H5: Perceived Usefulness has a significant influence on attitude.

6. Attitude (ATT)

Attitude refers to an individual's overall evaluation of a behavior as favorable or unfavorable (Ajzen, 1991; Ajzen & Fishbein, 1980). In food delivery service systems (FDSS), it reflects students' evaluation of the platform based on accumulated experience rather than initial impressions. As users gain experience, their attitudes become more stable through consistent service performance and fulfillment of expectations (Bhattacharjee & Premkumar, 2004; Venkatesh et al., 2012).

In technology acceptance research, attitude links users' beliefs and behavioral intention. Perceived usefulness and perceived ease of use shape evaluative judgments, which influence intention to use a system (King & He, 2006; Schierz et al., 2010). Emotional responses such as enjoyment and satisfaction may further strengthen users' evaluations of digital platforms (Lowry et al., 2013; Van der Heijden, 2004). As satisfaction increases and uncertainty decreases, users are more likely to develop positive attitudes toward online services (Gefen et al., 2003). Recent research on food delivery services also confirms that consumer attitudes play a critical role in shaping purchase and usage intentions (Al Maalouf et al., 2025). Therefore, attitude is considered an important predictor of intention to use digital platforms (Kim et al., 2009; Toft et al., 2014).

H6: Attitude has a significant influence on intention to use.

7. Intention to Use (ITU)

Intention to use refers to the degree of willingness or plan a person has to perform a behavior and is widely regarded as a predictor of actual behavior (Ajzen, 1991; Fishbein & Ajzen, 1975). In food delivery service systems (FDSS), sophomore students' intention reflects

their decision to continue using the platform based on prior experience and expectations of service reliability and benefits (Bhattacharjee & Premkumar, 2004).

According to the Technology Acceptance Model, behavioral intention is influenced by attitude and belief constructs such as perceived usefulness and perceived ease of use (Davis et al., 1989; Venkatesh & Davis, 2000). Studies in mobile commerce and online services also show that favorable attitudes increase users' intention to continue using digital platforms (King & He, 2006; Schierz et al., 2010).

In post-adoption contexts, intention reflects users' evaluation of long-term service value rather than initial curiosity (Raman & Aashish, 2021). It is also influenced by satisfaction and consistent service performance in online environments (Gefen et al., 2003; Pavlou, 2003).

Research Framework

This study proposes a framework to examine how sophomore students evaluate food delivery service systems (FDSS) and how these evaluations influence their intention to use the platforms. Compared with first-year users, second-year students form judgments based on accumulated experience. The model follows a belief–evaluation–intention structure derived from technology acceptance and behavioral intention theories (Ajzen, 1991; Davis, 1989; Venkatesh et al., 2003).

The framework includes compatibility, emotion, performance expectancy, perceived ease of use, and perceived usefulness. Compatibility influences attitude because alignment with routines supports positive evaluation (Rogers, 1995). Emotion shapes attitude through affective responses from repeated service interactions. Performance expectancy reflects perceived efficiency gains (Venkatesh et al., 2003). Perceived ease of use and perceived usefulness influence attitude by shaping effort and value perceptions (Davis, 1989).

Attitude is modeled as the sole direct predictor of intention based on the Theory of Planned Behavior (Ajzen, 1991), with other factors acting through it. Trust, satisfaction, and habit are excluded to maintain model focus and avoid conceptual overlap.

The framework extends TAM and UTAUT by integrating emotional and compatibility factors in a post-adoption context, emphasizing experiential evaluation among experienced users.

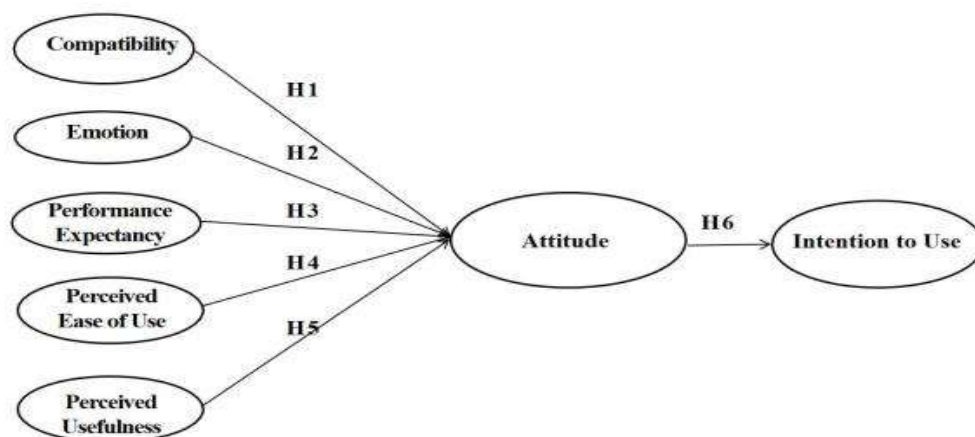


Figure 1 Conceptual Framework

Research Methodology

This study adopts a quantitative research design to examine how sophomore students' perceptions of food delivery service systems (FDSS) influence their intention to use the platforms. A descriptive research approach was applied to analyze students' evaluations and behavioral intentions without experimental manipulation (Sekaran & Bougie, 2016).

Data were collected using an online structured questionnaire developed based on the study's theoretical framework. The questionnaire was distributed through online channels such as WeChat and class communication groups, and measures such as restricting one response per device were applied to reduce duplicate submissions. The measurement items were first evaluated by experts using the Index of Item–Objective Congruence (IOC) to ensure content validity. The constructs were measured using a five-point Likert scale.

Participation was voluntary, and informed consent was obtained from all respondents before completing the survey. Only second-year vocational college students with prior experience using food delivery platforms were included in the study. A pilot survey was conducted to assess the reliability of the measurement scales, and all constructs achieved Cronbach's alpha values above 0.70, indicating acceptable internal consistency.

Structural Equation Modeling was performed using SPSS AMOS (Version 26) to analyze the data and examine the relationships among the constructs, as it allows simultaneous evaluation of measurement validity and structural relationships within the proposed model (Hair et al., 2013).

1. Research Population and Sample Size

The population of this study consisted of sophomore students at Liaoning Railway Vocational and Technical College in China. The study focused on three departments: Railway Transportation (330 students), Railway Vehicle Technology (411 students), and

Electrical Engineering and Information (485 students), with a total sophomore population of 1,226 students.

Following recommendations for Structural Equation Modeling, a minimum sample size of 200 is generally required for stable estimation (Hair et al., 2013; Kline, 2016). To enhance reliability, this study targeted a sample size of 500 students.

Non-probability sampling was applied. Judgmental sampling was used to identify relevant departments where students frequently use food delivery services. These three departments were selected because they represent major academic disciplines within the institution and include students with regular exposure to digital platforms and online services, making them suitable for examining food delivery usage behavior. Quota allocation was then used to distribute the sample proportionally across the three departments, resulting in 135, 168, and 197 respondents respectively. Convenience sampling was used to distribute the online questionnaires to eligible students.

Results and Discussion

1. Demographic Information

The sample consisted of 500 sophomore students from Liaoning Railway Vocational and Technical College. Male students represented the majority of respondents, accounting for 83.8% (419 students), while female students accounted for 16.2% (81 students). All participants were second-year students, ensuring consistency in academic level.

Regarding experience with food delivery services, most respondents reported relatively long usage. A total of 86.6% (433 students) had three to four years of experience using food delivery platforms, while 13.4% (67 students) had one to two years of experience. This indicates that the majority of respondents were familiar with food delivery service systems and had accumulated sufficient experience to evaluate their usage and benefits.

2. Confirmatory Factor Analysis (CFA)

Confirmatory factor analysis (CFA) was conducted to assess the validity and reliability of the measurement model. The analysis focused on factor loadings, internal consistency, and convergent validity. As shown in Table 3, all measurement items loaded significantly on their respective constructs, with standardized factor loadings ranging from 0.750 to 0.902. Reliability was confirmed as Cronbach's alpha and composite reliability values for all constructs exceeded the recommended threshold of 0.70. Convergent validity was also established, as the average variance extracted (AVE) values ranged from 0.609 to 0.757, exceeding the minimum criterion of 0.50 (Fornell & Larcker, 1981). These results indicate that the constructs adequately explain the variance of their indicators.

Discriminant validity was evaluated using the Fornell–Larcker criterion. As presented in Table 4, the square root of the AVE for each construct was greater than its correlation with other constructs, confirming satisfactory discriminant validity.

The goodness-of-fit indices in Table 5 indicate that the measurement model fits the data well. All fit indices meet the recommended thresholds, including CMIN/df, GFI, AGFI, NFI, CFI, TLI, and RMSEA. These results suggest that the measurement model is reliable and suitable for testing the structural relationships.

Table 1 Confirmatory Factor Analysis Results

Variable	Source of Questionnaire (Measurement Indicator)	No. of Item	Cronbach's Alpha	Factor Loading	CR	AVE
COM	Hwang et al. (2019)	3	0.845	0.779-0.817	0.846	0.646
EM	Hwang et al. (2019)	3	0.903	0.829-0.895	0.903	0.757
PE	Allah Pitchay et al. (2022)	5	0.898	0.768-0.820	0.899	0.640
PEOU	Kumar et al. (2024)	3	0.882	0.791-0.902	0.885	0.721
PU	Kumar et al. (2024)	3	0.846	0.777-0.827	0.847	0.649
ATT	Allah Pitchay et al. (2022)	4	0.861	0.750-0.798	0.862	0.609
ITU	Kumar et al. (2024)	3	0.842	0.774-0.826	0.845	0.645

Note: Composite Reliability (CR); and Average Variance Extracted (AVE)

Table 2 Discriminant Validity

Variable	COM	EM	PE	PEOU	PU	ATT	ITU
COM	0.803						
EM	0.392	0.870					
PE	0.175	0.218	0.800				
PEOU	0.177	0.274	0.086	0.849			
PU	0.134	0.220	0.143	0.216	0.805		
ATT	0.371	0.402	0.248	0.297	0.322	0.780	
ITU	0.400	0.467	0.308	0.382	0.369	0.491	0.803

Note: The diagonally listed value is the AVE square roots of the variables

Table 3 Goodness of Fit for Measurement and Structural Model

Fit Index	Recommended Value and Source	CFA Value	SEM Value
CMIN/df	< 5.00 (Awang, 2012)	1.546	2.716
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.945	0.892
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.929	0.868
NFI	≥ 0.80 (Wu & Wang, 2006)	0.949	0.904
CFI	≥ 0.80 (Bentler, 1990)	0.981	0.937
TLI	≥ 0.80 (Sharma et al., 2005)	0.978	0.929
RMSEA	< 0.08 (Pedroso et al., 2016)	0.033	0.059

Note: CMIN/df = The ratio of the chi-square value to degree of freedom, GFI = goodness-of-fit index, AGFI = adjusted goodness-of-fit index, TLI = Tucker Lewis index, NFI = normalized fit index, CFI = comparative fit index, RMSEA = root mean square error of approximation

3. Structural Equation Model (SEM)

Structural Equation Modeling (SEM) was conducted using SPSS AMOS to examine the hypothesized relationships among the constructs. SEM is suitable for analyzing relationships among latent variables within a single theoretical model. The structural relationships among the constructs are illustrated in Figure 2.

As presented in Table 3, the model fit indices meet the recommended thresholds, indicating an acceptable fit between the structural model and the observed data. These results suggest that the proposed model adequately represents the relationships among the constructs and is appropriate for testing the research hypotheses.

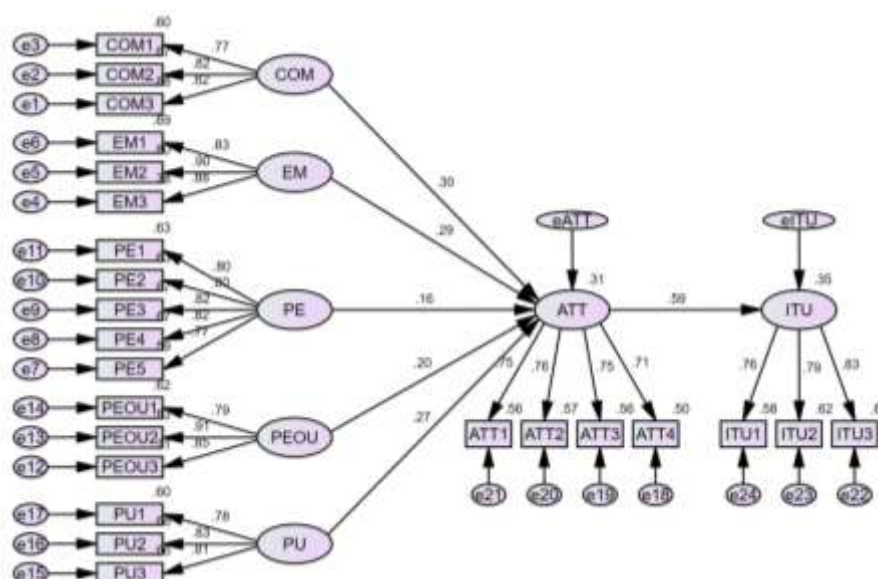


Figure 2 Structural Model

4. Research Hypothesis Testing Result

The proposed hypotheses were tested using structural equation modeling based on the sophomore sample. The results are summarized in Table 4. All hypothesized paths were statistically significant at $p < 0.001$, indicating strong support for the proposed relationships.

Table 4: Hypothesis Testing Result

Hypothesis	Standardized Estimate (β)	t-Value	Result
H1: COM $\rightarrow$ ATT	0.296	5.976***	Supported
H2: EM $\rightarrow$ ATT	0.285	6.031***	Supported
H3: PE $\rightarrow$ ATT	0.162	3.507***	Supported
H4: PEOU $\rightarrow$ ATT	0.204	4.386***	Supported
H5: PU $\rightarrow$ ATT	0.271	5.531***	Supported
H6: ATT $\rightarrow$ ITU	0.589	10.411***	Supported

Note: *** $p < 0.001$

Compatibility had a significant positive influence on attitude (H1, $\beta = 0.296$, $t = 5.976$). This result suggests that when food delivery service systems fit well with students' daily routines and consumption habits, they are more likely to develop favorable attitudes toward the platforms.

Emotion also showed a significant positive effect on attitude (H2, $\beta = 0.285$, $t = 6.031$). This indicates that positive emotional experiences, such as enjoyment and satisfaction during service use, contribute to more favorable evaluations of the platform.

Performance expectancy had a significant positive influence on attitude (H3, $\beta = 0.162$, $t = 3.507$). Although the effect is smaller than other factors, it indicates that perceived performance benefits still contribute to students' evaluations of the service.

Perceived ease of use also positively influenced attitude (H4, $\beta = 0.204$, $t = 4.386$), suggesting that smooth and effortless system interaction remains important even for experienced users.

Perceived usefulness demonstrated a significant positive influence on attitude (H5, $\beta = 0.271$, $t = 5.531$), indicating that students value the practical benefits and efficiency provided by food delivery platforms.

Finally, attitude had a strong positive effect on intention to use (H6, $\beta = 0.589$, $t = 10.411$). This finding confirms that favorable attitudes play a central role in translating students' perceptions and experiences into continued intention to use the service.

The model explains 31.0% of the variance in attitude ($R^2 = 0.310$) and 34.7% of the variance in intention to use ($R^2 = 0.347$), indicating a moderate level of explanatory power

for the proposed relationships. These values suggest that while the model explains a meaningful proportion of variance, additional factors may further improve its explanatory power.

Conclusions, Recommendations, Limitations and Future Research

1. Conclusions

This study applied a quantitative research design using structural equation modeling to examine the factors influencing sophomore students' intention to use food delivery service systems (FDSS). The objective was to investigate how compatibility, emotion, performance expectancy, perceived ease of use, and perceived usefulness influence students' attitudes and how attitude affects intention to use the platforms. The study contributes by extending technology acceptance research into the post-adoption stage, where user evaluations are shaped by accumulated experience rather than initial perceptions.

The results show that compatibility and emotion are the most influential factors shaping students' attitudes toward FDSS. Compatibility reflects how well the service fits students' daily routines and consumption habits, and its importance increases as users gain more experience with digital platforms (Moore & Benbasat, 1991; Rogers, 2003). Emotion also plays a strong role. Positive experiences such as enjoyment and satisfaction strengthen users' evaluations of digital services (Lowry et al., 2013; Van der Heijden, 2004). This suggests that experienced users rely more on affective responses and routine alignment, as repeated interactions reduce uncertainty and shift evaluation toward experiential judgment. These findings are consistent with recent studies on food delivery platforms that emphasize the role of emotional satisfaction in shaping user attitudes (Hwang et al., 2019).

Performance expectancy, perceived ease of use, and perceived usefulness also significantly affected attitude, although their influence was relatively smaller. This can be explained by habituation effects. As users become familiar with the system, they view functional features as basic requirements rather than distinguishing factors. As a result, their influence on attitude decreases over time. This pattern differs from early adoption studies, where usefulness and ease of use are often dominant predictors (Davis, 1989; Venkatesh et al., 2003), indicating a shift in evaluation criteria in the post-adoption stage.

Finally, attitude emerged as the strongest predictor of intention to use, confirming its central role in technology adoption behavior (Ajzen, 1991; Fishbein & Ajzen, 1975). Overall, the findings suggest that continued usage is driven more by experiential and lifestyle factors than by functional attributes, clarifying sustained engagement with digital services.

2. Recommendations

Food delivery platforms should focus on sustaining sophomore students' long term engagement with the service. Since compatibility significantly influences attitude, service features should align with students' daily routines. For example, platforms may introduce subscription plans, scheduled delivery options, or student oriented meal packages that match common study schedules and campus lifestyles. Platforms may also collaborate with campus canteens and nearby restaurants to offer time based promotions or bundled meal options that fit students' daily schedules.

Platforms should also strengthen emotional engagement because positive emotional experiences were found to significantly influence attitude. Interactive features, loyalty programs, and personalized recommendations can enhance enjoyment and satisfaction during service use. Gamified rewards, personalized push notifications, and targeted discounts based on past orders can further increase user engagement and retention. These strategies can help maintain positive user experiences and encourage continued platform usage.

In addition, platforms should maintain stable system performance and reliable service quality. Although ease of use may become less critical as students gain experience, system stability and consistent service performance remain important to prevent user frustration and dissatisfaction. Managers should prioritize delivery accuracy, reduce waiting time, and ensure responsive customer service to maintain trust and service reliability. Ensuring reliable delivery, accurate order processing, and responsive platform performance can therefore support students' favorable attitudes and strengthen their intention to continue using food delivery services.

3. Limitations and Future Research

This study has several limitations. First, the research was conducted in a single institution within one regional context and focused only on sophomore students. The use of non-probability sampling methods, including judgmental, quota, and convenience sampling, may limit the generalizability of the findings. In addition, the sample shows a gender imbalance, which may influence the representativeness of the results. Future studies may include multiple institutions or different regional contexts to improve generalizability.

Second, the cross-sectional design limits the ability to observe how students' motivations and perceptions change over time. Future research may adopt longitudinal designs or multi-group comparisons to examine how attitudes and intention to use evolve across different student groups or stages of study.

Third, the study examined a limited number of constructs from technology acceptance theories. Additional factors such as trust, service quality, or perceived risk may also influence continued platform usage. Furthermore, as the data were collected using a self-reported questionnaire, there is a possibility of common method bias, which may affect

the results. Future research may incorporate additional variables and apply different data collection methods to provide a more comprehensive explanation of continued use of food delivery platforms.

Reference

- Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, 50(2), 179–211. [https://doi.org/10.1016/0749-5978\(91\)90020-T](https://doi.org/10.1016/0749-5978(91)90020-T)
- Ajzen, I., & Fishbein, M. (1980). *Understanding attitudes and predicting social behavior*. Prentice-Hall.
- Allah Pitchay, A., Ganesan, Y., Zulkifli, N. S., & Khaliq, A. (2022). Determinants of customers' intention to use online food delivery applications through smartphones in Malaysia. *British Food Journal*, 124(3), 732–753. <https://doi.org/10.1108/BFJ-01-2021-0075>
- Al Maalouf, N. J., Mourad, M., & El Manzani, Y. (2025). Consumers' attitudes and purchase intentions toward food delivery services. *Journal of Retailing and Consumer Services*, 84, 104151. <https://doi.org/10.1016/j.jretconser.2024.104151>
- Al-Qudah, A. A., Al-Okaily, M., Alqudah, H., & Alkasasbeh, O. (2024). Determinants of digital payment adoption among consumers. *Journal of Risk and Financial Management*, 17(11), 521. <https://doi.org/10.3390/jrfm17110521>
- Awang, Z. (2012). *Structural equation modeling using AMOS graphic*. Penerbit Universiti Teknologi MARA.
- Ayo, C. K., Oni, A. A., Adewoye, O. J., & Eweoya, I. O. (2016). E-banking users' behaviour: E-service quality, attitude, and customer satisfaction. *International Journal of Bank Marketing*, 34(3), 347–367. <https://doi.org/10.1108/IJBM-12-2014-0175>
- Baca, G., & Zhushi, G. (2025). Assessing attitudes and impact of AI integration in higher education. *Higher Education, Skills and Work-Based Learning*, 15(2), 369–383. <https://doi.org/10.1108/HESWBL-02-2024-0065>
- Bagozzi, R. P., Gopinath, M., & Nyer, P. U. (1999). The role of emotions in marketing. *Journal of the Academy of Marketing Science*, 27(2), 184–206. <https://doi.org/10.1177/0092070399272005>
- Bentler, P. M. (1990). Comparative fit indexes in structural models. *Psychological Bulletin*, 107(2), 238–246. <https://doi.org/10.1037/0033-2909.107.2.238>
- Bettiga, D., & Lamberti, L. (2018). Exploring the role of anticipated emotions in product adoption and usage. *Journal of Consumer Marketing*, 35(3), 300–316. <https://doi.org/10.1108/JCM-06-2016-1860>
- Bhattacharjee, A., & Premkumar, G. (2004). Understanding changes in belief and attitude toward information technology usage: A theoretical model and longitudinal test. *MIS Quarterly*, 28(2), 229–254. <https://doi.org/10.2307/25148634>

- Chin, T. (2014). Harmony as a means to enhance affective commitment in a Chinese organization. *Cross Cultural Management: An International Journal*, 21(3), 326–344. <https://doi.org/10.1108/CCM-05-2012-0038>
- China Internet Network Information Center. (2023). *The 53rd statistical report on internet development in China*. <http://www.cnnic.net.cn/>
- Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 13(3), 319–340. <https://doi.org/10.2307/249008>
- Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). User acceptance of computer technology: A comparison of two theoretical models. *Management Science*, 35(8), 982–1003. <https://doi.org/10.1287/mnsc.35.8.982>
- Fishbein, M., & Ajzen, I. (1975). *Belief, attitude, intention, and behavior: An introduction to theory and research*. Addison-Wesley.
- Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, 18(1), 39–50. <https://doi.org/10.1177/002224378101800104>
- Gefen, D., Karahanna, E., & Straub, D. W. (2003). Trust and TAM in online shopping: An integrated model. *MIS Quarterly*, 27(1), 51–90. <https://doi.org/10.2307/30036519>
- Gefen, D., & Straub, D. W. (2000). The relative importance of perceived ease of use in IS adoption: A study of e-commerce adoption. *Journal of the Association for Information Systems*, 1(1), Article 8. <https://doi.org/10.17705/1jais.00008>
- Hair, J. F., Ringle, C. M., & Sarstedt, M. (2013). Partial least squares structural equation modeling: Rigorous applications, better results and higher acceptance. *Long Range Planning*, 46(1–2), 1–12. <https://doi.org/10.1016/j.lrp.2013.01.001>
- Ham, J., Li, S., Looi, J., & Eastin, M. S. (2024). Virtual humans as social actors: Investigating user perceptions of virtual humans' emotional expression on social media. *Computers in Human Behavior*, 155, 108161. <https://doi.org/10.1016/j.chb.2024.108161>
- Hwang, J., Lee, J. S., & Kim, H. (2019). Perceived innovativeness of drone food delivery services and its impacts on attitude and behavioral intentions: The moderating role of gender and age. *International Journal of Hospitality Management*, 81, 94–103. <https://doi.org/10.1016/j.ijhm.2019.03.002>
- Kim, H.-W., Chan, H. C., & Gupta, S. (2009). Value-based adoption of mobile internet: An empirical investigation. *Decision Support Systems*, 43(1), 111–126. <https://doi.org/10.1016/j.dss.2005.05.009>
- King, W. R., & He, J. (2006). A meta-analysis of the technology acceptance model. *Information & Management*, 43(6), 740–755. <https://doi.org/10.1016/j.im.2006.05.003>

- Kleinginna, P. R., & Kleinginna, A. M. (1981). A categorized list of emotion definitions, with suggestions for a consensual definition. *Motivation and Emotion*, 5(4), 345–379. <https://doi.org/10.1007/BF00992553>
- Kline, R. B. (2016). *Principles and practice of structural equation modeling* (4th ed.). Guilford Press.
- Kumar, A., Singh, R., & Dwivedi, Y. K. (2024). Re-examining the role of perceived usefulness in digital adoption: Evidence from emerging markets. *Journal of Business Research*, 172, 114123.
- Labrecque, J. S., Wood, W., Neal, D. T., & Harrington, N. (2017). Habit slips: When consumers unintentionally resist new products. *Journal of the Academy of Marketing Science*, 45(1), 119–133. <https://doi.org/10.1007/s11747-016-0482-9>
- Lee, H.-H., Fiore, A. M., & Kim, J. (2006). The role of the technology acceptance model in explaining effects of image interactivity technology on consumer responses. *International Journal of Retail & Distribution Management*, 34(8), 621–644. <https://doi.org/10.1108/09590550610675949>
- Lowry, P. B., Gaskin, J., Twyman, N. W., Hammer, B., & Roberts, T. L. (2013). Taking “fun and games” seriously: Proposing the hedonic-motivation system adoption model (HMSAM). *Journal of the Association for Information Systems*, 14(11), 617–671. <https://doi.org/10.17705/1jais.00347>
- Martensen, A., & Grønholdt, L. (2016). The effect of word-of-mouth on consumer emotions and choice: Findings from a service industry. *International Journal of Quality and Service Sciences*, 8(3), 298–314. <https://doi.org/10.1108/IJQSS-04-2016-0037>
- Moore, G. C., & Benbasat, I. (1991). Development of an instrument to measure the perceptions of adopting an information technology innovation. *Information Systems Research*, 2(3), 192–222. <https://doi.org/10.1287/isre.2.3.192>
- Munday, M. R., Chuchu, T., & Mafini, C. (2024). Determining the drivers of continued mobile food delivery app (MFDA) usage during a pandemic period. *Cogent Business & Management*, 11(1), Article 2308086. <https://doi.org/10.1080/23311975.2024.2308086>
- Palas, J., Sorwar, G., Hoque, M., & Sivabalan, A. (2022). Factors influencing the elderly’s adoption of mHealth: An empirical study using the extended UTAUT2 model. *BMC Medical Informatics and Decision Making*, 22, Article 191. <https://doi.org/10.1186/s12911-022-01917-3>
- Pavlou, P. A. (2003). Consumer acceptance of electronic commerce: Integrating trust and risk with the technology acceptance model. *International Journal of Electronic Commerce*, 7(3), 101–134. <https://doi.org/10.1080/10864415.2003.11044275>

- Pedroso, B., Garcia, R., & Scott, D. (2016). Assessing model fit in structural equation modeling: A Monte Carlo simulation. *International Journal of Statistics and Probability*, 5(3), 1–10.
- Püschel, J., Mazzon, J. A., & Hernandez, J. M. C. (2010). Mobile banking: Proposition of an integrated adoption intention framework. *International Journal of Bank Marketing*, 28(5), 389–409. <https://doi.org/10.1108/02652321011064908>
- Raman, P., & Aashish, K. (2021). To continue or not to continue: A structural analysis of antecedents of mobile payment systems in India. *International Journal of Bank Marketing*, 39(2), 242–271. <https://doi.org/10.1108/IJBM-04-2020-0167>
- Riedel, A., Mulcahy, R., & Northey, G. (2022). Feeling the love? How consumers' political ideology shapes responses to AI financial service delivery. *International Journal of Bank Marketing*, 40(6), 1102–1132. <https://doi.org/10.1108/IJBM-09-2021-0438>
- Rogers, E. M. (1995). *Diffusion of innovations* (4th ed.). Free Press.
- Rogers, E. M. (2003). *Diffusion of innovations* (5th ed.). Free Press.
- Schierz, P. G., Schilke, O., & Wirtz, B. W. (2010). Understanding consumer acceptance of mobile payment services: An empirical analysis. *Electronic Commerce Research and Applications*, 9(3), 209–216. <https://doi.org/10.1016/j.elerap.2009.07.005>
- Sekaran, U., & Bougie, R. (2016). *Research methods for business: A skill-building approach* (7th ed.). Wiley.
- Sharma, S., Mukherjee, S., Kumar, A., & Dillon, W. R. (2005). A simulation study to investigate the use of cutoff values for assessing model fit in covariance structure models. *Journal of Business Research*, 58(7), 935–943. <https://doi.org/10.1016/j.jbusres.2003.10.007>
- Sica, C., & Ghisi, M. (2007). The Italian versions of the Beck Anxiety Inventory and the Beck Depression Inventory-II: Psychometric properties and discriminant power. *Behavioural and Cognitive Psychotherapy*, 35(4), 541–555.
- Toft, M. B., Schuitema, G., & Thøgersen, J. (2014). Responsible technology acceptance: Model development and application to consumer acceptance of smart grid technology. *Applied Energy*, 134, 392–400. <https://doi.org/10.1016/j.apenergy.2014.08.048>
- Van der Heijden, H. (2004). User acceptance of hedonic information systems. *MIS Quarterly*, 28(4), 695–704. <https://doi.org/10.2307/25148660>
- Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management Science*, 46(2), 186–204. <https://doi.org/10.1287/mnsc.46.2.186.11926>
- Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, 27(3), 425–478. <https://doi.org/10.2307/30036540>

- Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *MIS Quarterly*, 36(1), 157–178. <https://doi.org/10.2307/41410412>
- Wang, S., Li, J., & Zhao, D. (2017). Understanding the intention to use medical big data processing technique from the perspective of medical data analysts. *Information Discovery and Delivery*, 45(4), 194–201. <https://doi.org/10.1108/IDD-03-2017-0017>
- Wu, J.-H., & Wang, S.-C. (2006). Measuring KMS success: A respecification of the DeLone and McLean model. *Information & Management*, 43(6), 728–739. <https://doi.org/10.1016/j.im.2006.05.002>
- Yang, K. (2010). Determinants of US consumer mobile shopping services adoption: Implications for designing mobile shopping services. *Journal of Consumer Marketing*, 27(3), 262–270. <https://doi.org/10.1108/07363761011038338>