İŞLETME ARAŞTIRMALARI DERGİSİ
JOURNAL OF BUSINESS RESEARCH-TURK
2025, 17(1), 172-186
https://doi.org/10.20491/isarder.2025.1964

Post-COVID-19 Dorm Students' Food Delivery E-commerce Use And Satisfaction: Insights From Theory of Planned Behavior and Technology Acceptance Model

Can SAYGINER [a]

[a]Izmir Democracy University, Faculty of Economics and Administrative Science, Department of Management Information Systems, Izmir, Türkiye. can.sayginer@idu.edu.tr

ARTICLE INFO

Keywords:

Food Delivery E-commerce Platforms
Theory of Planned Behavior (TPB) Model
Technology Acceptance Model (TAM)
Dorm Students
Post-COVID19

Received 2 July 2024
Revised 29 December 2024
Accepted 5 January 2025

Article Classification:
Research Article

ABSTRACT

Purpose – The research aims to investigate the behavioral intentions of dorm students in Izmir, Turkey towards a food delivery e-commerce platform, utilizing the Theory of Planned Behavior (TPB) and the Technology Acceptance Model (TAM) in the post-COVID19 era.

Design/methodology/approach - Data from 224 dorm students were collected via a structured Google Forms questionnaire and analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS 3.0. Confirmatory factor analysis was applied to measure the structural model.

Findings - Actual use (AU), item-information quality (IQ), and hedonic motivation (HM) significantly affect overall satisfaction and loyalty (S&L). Hedonic motivation refers to the enjoyment of using the platform, while the quality of the item information reflects the accuracy and reliability of the information provided. The analysis showed that hedonic motivation, information quality of TPB, and TAM's actual use explained 75.10% of the variance in satisfaction. The variance of price to sale (PS), restaurant credibility (RC), and navigational design (ND) explained 69.0% of the variance of information-item quality (IQ). Intention to use (ITU) explained 57.7% of the variance of the actual use (AU).

Discussion - The findings suggest that e-commerce platforms can boost user engagement and satisfaction by improving navigational design and aligning with dorm students' hedonic motivations, thus enhancing loyalty and reuse. The post-COVID-19 era is dramatically changing consumer behavior and increasing trust in digital platforms for safety and convenience. The research contributes insights into dorm students' online food delivery behavior, emphasizing the importance of user satisfaction and loyalty in digital commerce and providing actionable strategies for service enhancement.

1. Introduction

The advent of digital technology and the rapid expansion of e-commerce have transformed the way consumers interact with businesses and make purchasing decisions (Turban et al., 2017). One sector that has experienced significant disruption is the food delivery industry, with the proliferation of Food Delivery e-commerce Platforms offering convenient and diverse culinary options. Understanding consumer behavior on these platforms, especially among university students, has become a topic of considerable interest to scholars and industry practitioners alike.

The adoption of Information and Communication Technologies (ICT) has revolutionized the food delivery industry, giving rise to various e-commerce platforms that offer convenience and efficiency in ordering food online. Regional and cultural factors such as preference for traditional Turkish cuisine and communal dining habits play an important role in shaping the use of these platforms, especially among young people. In the post-COVID19 era, the reliance on digital platforms for basic services is further emphasized. The pandemic has not only changed consumer preferences, but also highlighted the important role that health and safety concerns play in behavior: Davis' (1989) Technology Acceptance Model (TAM) and Ajzen's (1991) Theory of Planned Behavior (TPB) stand out among various frameworks explaining ICT adoption due to their relevance in understanding user behavior when used on food delivery e-commerce platforms. These models focus on the key determinants of technology adoption and provide a comprehensive and concise framework for this study.

The TPB, developed by Ajzen (1991), includes three core components: attitudes, subjective norms, and perceived behavioral control, all posited to affect individuals' intentions to perform a behavior. The model has

Suggested Citation
Saygıner, C. (2024). Post-COVID-19 Dorm Students' Food Delivery E-commerce Use And Satisfaction: Insights From Theory Of Planned Behavior and Technology Acceptance Model, Journal of Business Research-Turk, 17 (1), 172-186.

been widely applied to investigate behavioral intentions in digital and academic contexts (Taylor and Todd, 1995; Pillai et al., 2022).

While TAM and TPB form the theoretical backbone of this study, additional insights from community-based research emphasize the importance of understanding the socio-economic and cultural dynamics of ICT adoption. In the context of technology use, TPB has been utilized to understand how social influences and control beliefs impact user adoption (Taylor and Todd, 1995). Pillai et al. (2022) utilized TPB to assess university students' intentions to use e-learning systems, highlighting the model's applicability in academic environments. TAM Framework proposed by Davis (1989), has been widely used to understand the acceptance and use of various technologies, including e-commerce platforms. The model suggests that perceived ease of use and usefulness are fundamental determinants of technology acceptance and usage intention (Davis, 1989). In the field of e-commerce, TAM has been extended to include trust and perceived risk, which are important for online transactions (Gefen et al., 2003).

Several studies have applied the TPB framework to comprehend the determinants of consumer intentions. TPB's model suggests that individuals who have a favorable attitude toward using such platforms perceive social approval (subjective norm), and believe they have control over the action are more likely to intend to use these services. These constructs have been shown to effectively predict behavioral intentions in food delivery services (Pillai et al., 2022; Longgang and Ming, 2023). For university students, particularly boarding students, this semester presented unique challenges, with restricted mobility and increased reliance on food delivery platforms for convenience and safety. Examining their behavior in the post-pandemic context offers important insights into how digital platforms are evolving to meet the needs of the population, especially the younger and tech-savvy.

Hedonic motivation and convenience motivation are two key elements often explored within the TPB framework when examining consumers' intentions to use food delivery e-commerce platforms. Hedonic motivation relates to the pleasure and enjoyment individuals derive from the experience of using these platforms. It encompasses factors such as the variety of cuisines available, the excitement of trying new foods, and the enjoyment of the ordering process itself (Prasetyo et al., 2021). For university students, the hedonic aspect of food delivery can be particularly appealing as it aligns with their desire for convenient yet enjoyable dining experiences. Convenience motivation, on the other hand, pertains to the time-saving and ease-of-use aspects of food delivery platforms. University students, often juggling academic commitments and tight schedules, highly value the convenience offered by these services (Longgang and Ming, 2023). Several studies have also applied the TAM framework to comprehend the determinants of consumer intentions by checking perceived ease of use and perceived usefulness. For example, a study by Kim et al. (2009) incorporated these elements into TAM, finding that they significantly influence users' willingness to engage in online purchasing behaviors. Integrated TAM and TPB Models has been proposed to provide a more comprehensive understanding of technology adoption behaviors. Venkatesh and Davis (2000) introduced the decomposed TPB, which includes elements from both TAM and TPB, suggesting that this integrated model could better account for a wide range of influences on technology usage intentions. TAM primarily focuses on perceived usefulness and ease of use as determinants of technology acceptance, while TPB emphasizes the role of attitudes towards behavior and subjective norms. By integrating these two, your study can offer a more comprehensive insight into both the cognitive and social influences on behavioral intentions.

The researches focuses on the COVID-19 period, highlighting various aspects of consumer behavior and industry response during the pandemic. Roe and Smith (2021) investigated the use of crowdfunding by restaurants during the COVID-19 pandemic. The research focused on donation-based campaigns without rewards, analyzing how social embeddedness and social capital affect the fundraising success of restaurants. Biswas and Verma (2022) examined the relationship between various dimensions of perceived service quality (like tangibility, reliability, empathy, responsiveness, and assurance), restaurant image, food quality, perceived value, and their impact on customer satisfaction in the Indian restaurant industry. Bordelon et al. (2021) examined the effects of the FDA's relaxed food labeling regulations on the food allergy community. Zapata-Cuervo et al. (2021) presented an in-depth analysis of how the restaurant industry in Colombia adapted to the challenges posed by the COVID-19 pandemic. Ali et al. (2020) study investigated factors influencing Pakistani consumers' intentions and behaviors regarding OFDO services during the COVID-19 pandemic. Herrera and Young (2022) study focused on the impact of customer suspicion on restaurants' revenue management strategies, specifically peak-load pricing. Byrd et al. (2021)'s study investigated the factors influencing restaurant patronage during the pandemic. However, there appears to be a gap in the literature regarding the post-COVID-19 period, particularly in understanding how consumer behavior, satisfaction, and loyalty in the food service industry have evolved as the world transitions out of the pandemic. Studies addressing changes in consumer preferences, industry adaptation strategies, and the long-term impacts of the pandemic on the food service sector, especially in the context of e-commerce platforms and technology acceptance among university students, would be valuable contributions to the field. This gap presents an opportunity for future research to explore the lasting effects of the pandemic and the evolving dynamics of the food service industry in the post-COVID-19 era. With a particular focus on university students living in dormitories, this study aims to determine how the behavioral patterns observed during the pandemic have persisted and what this means for the future of e-commerce platforms.

Turkey's youthful and tech-savvy populace is driving the country's online meal delivery market's rapid expansion (Statista.com, 2023). It was intentional to choose Izmir, a thriving city with a sizable student population, as the study's center. This group occupies a special niche where lifestyle demands and technological know-how collide to make food delivery services an essential part of day-to-day living. However, little is known about how TPB and TAM together can account for this group's behavioral intentions when it comes to food delivery platforms. By providing a thorough examination of how TPB and TAM components interact to influence students' intentions to use these platforms, this study seeks to close this gap. Using quantitative methods, the approach offers a comprehensive understanding of the variables affecting students' decision-making. By analyzing the interaction between TPB, TAM and local cultural factors, this study contributes to a better understanding of university students' e-commerce adoption.

In 2023, the Turkish online food delivery market is expected to generate US$4.31 billion in revenue and is anticipated to grow at a 16.94% annual rate (CAGR 2023–2027), with a projected market volume of US$8.06 billion by 2027 (Statista. com, 2023). The choice of Izmir, a vibrant city with a significant student population, as the study's locus, is deliberate. This demographic is uniquely positioned at the intersection of technological savviness and lifestyle needs that make food delivery services a vital aspect of daily life. However, existing literature offers limited insights into how TPB and TAM can collectively explain the behavioral intentions of this group in the context of food delivery platforms for the dorm students of universities. This study aims to bridge this gap by offering a comprehensive analysis of how TPB and TAM elements interplay in shaping students' intentions to use these platforms. The approach is quantitative methods, providing a holistic understanding of the factors influencing students' decision-making processes. The implications of this research are manifold. For students, it provides insights into their behavioral patterns. E-commerce platforms offer valuable information to tailor their services more effectively. Policy-makers and educational institutions can also benefit from understanding the needs and preferences of this significant demographic.

2. Method

This study employs a cross-sectional research design to investigate the behavioral intentions and actual use of Food Delivery e-commerce Platforms among university students in Izmir, Turkey. Data were collected between February 2023 and April 2024 at a point in time to provide insight into behavioral intentions, actual use and the factors influencing them. The research model was developed by using Prasetyo et al. (2021)'s scale, as shown in Appendix A.

The target population of the study consists of university students residing in dorms and attending classes at the education faculty in Izmir, Turkey. To choose a representative sample of university students, a convenience sampling technique is used. Owing to the heterogeneous student body, a wide range of academic disciplines are represented by the inclusion of these institutions.

Google Forms is the particular digital survey tool used for data collection. Student associations, social media, and university email lists are all used to invite people to take part in the survey. The goal of the study, the privacy of the data, and the voluntary nature of participation are all explained to participants.

The COVID-19 perceived severity construct (PSEV) measures how seriously students take the pandemic and how it might affect their behavior. To ascertain participants' intentions to use food delivery e-commerce platforms, the measure of intention to use (ITU) is employed. The "actual use" (AU) construct gauges how users use these platforms. Price to sales (PS) measures participants' perceptions and worries about the cost of purchasing the goods. Restaurant Credibility (RC) measures how much participants believe these platforms' restaurants are legitimate. The study of navigational design (ND) looks at how users interact with a platform and how easy it is to navigate. Convenience and time-saving factors have an impact on usage intentions, and this is measured by Convenience Motivation (CM). The perceived severity construct of COVID-19 (PSEV) assesses students' perception of the severity of the COVID-19 pandemic and its potential impact on their behavior. Intention to use (ITU) is measured to understand participants' intentions to use Food Delivery e-commerce Platforms. The actual use (AU) construct measures the actual usage behavior of participants on these platforms. Price to sales (PS) assesses participants' concerns and perceptions related to the price of buying the products. Restaurant Credibility (RC) evaluates participants' trust in the credibility of restaurants using these platforms. Navigational design (ND) examines participants' perceptions of the platform's user interface and navigational ease. Convenience motivation (CM) evaluates the degree to which convenience and time-saving factors influence usage intentions. The ease with which participants perceive using these platforms is measured by the Perceived Ease of Use (PEOU) measure. Item-Information Quality (IQ) evaluates the dependability, correctness, and comprehensiveness of the data on food delivery e-commerce platforms. Participant pleasure and enjoyment from these platforms are captured by hedonic motivation (HM). Participants' loyalty and satisfaction with the platforms are measured by Satisfaction and Loyalty (S&L). The research model was built as shown in Figure 1.

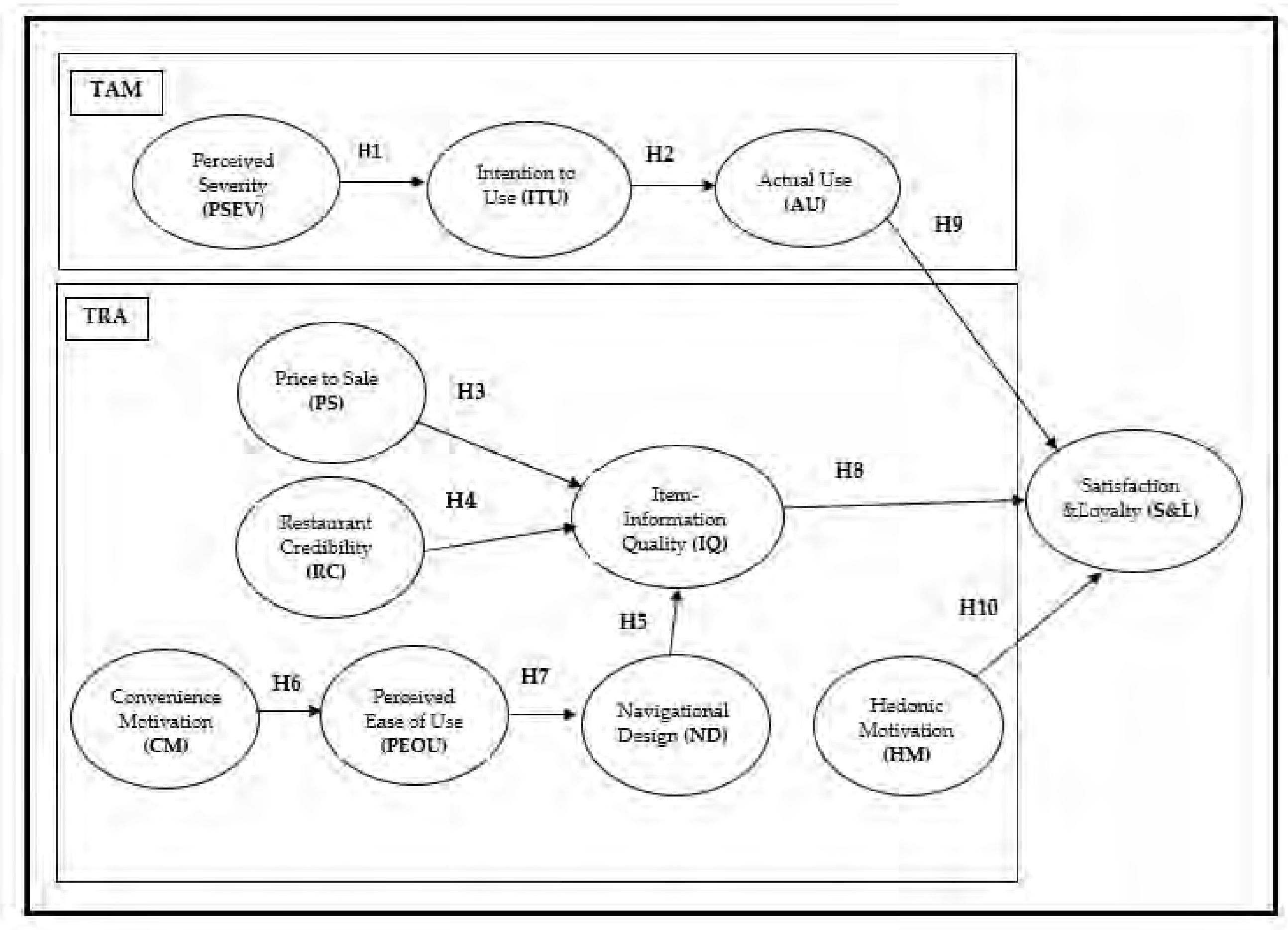

Figure 1. The Research Model (***Source:*** Author's own work)

Advanced statistical methods, such as partial least squares structural equation modeling (PLS-SEM) and structural equation modeling (SEM), are used in the analysis of data. PLS-SEM is selected because it can be used to analyze complex models with samples that range in size from small to medium (Hair et al., 2017). The analysis seeks to test the hypotheses, investigate the connections between the constructs, and obtain an understanding of the variables affecting behavioral intentions, actual use, satisfaction, and loyalty.

The study's hypotheses regarding how university dorm students in Izmir, Turkey, used food delivery platforms appear to be a combination of the Theory of Planned Behavior (TPB), the Technology Acceptance Model (TAM), and TAM extensions that take into account extra motivational factors.

H1: Perceived Severity and Intention to Use - An extension of TAM that takes into account outside factors that impact perceived utility and perceived ease of use—in this case, the perceived severity—may have an impact on this hypothesis. It is consistent with the health belief model, which asserts that behavioral intentions are influenced by the perceived seriousness of a health threat (Rosenstock, 1974).

H1. Perceived severity (PSEV) had a significant direct effect on intention to use (ITU).

H2: Intention to Use and Actual Use - In this case, the behavioral intention (ITU) determines the actual behavior (AU), and the TAM and TPB are directly applied (Ajzen, 1991; Davis, 1989).

H2. Intention to use (ITU) had a significant effect on actual use (AU).

H3, H4, and H5: The Impact of Item-Information Quality Navigational Design, Restaurant Credibility, and Price to Sales These theories, which have been examined in e-commerce and TAM research, highlight the significance of trust and system features on user perception (Pavlou, 2003; Wang and Benbasat, 2005).

H3. Price to sales (PS) had a significant direct effect on Item-Information Quality (IQ).

H4. Restaurant Credibility (RC) had a significant direct effect on Item-Information Quality (IQ).

H5. Navigational design (ND) had a significant direct effect on Item-Information Quality (IQ).

H6 and H7: Perceived Ease of Use and Convenience Motivation - These are related to TAM extensions that take into account motivational factors as predictors of perceived ease of use, which in turn influences system use (Venkatesh and Davis, 2000).

H6. Convenience motivation (CM) had a significant direct effect on Perceived ease of use **(PEOU).**

H7. Perceived ease of use (PEOU) had a significant direct effect on Navigational design (ND).

H8: Item-Information Quality on Satisfaction and Loyalty - The information systems success model (DeLone and McLean, 1992) asserts that item-information quality is a crucial factor in determining user satisfaction, which had an impact on this hypothesis.

H8. Item-Information Quality (IQ) had a significant direct effect on satisfaction and loyalty (S&L).

H9: Actual Use on Satisfaction and Loyalty – According to Hypothesis 9, using a system affects user satisfaction, which in turn promotes loyalty. This concept is consistent with Oliver's expectation-confirmation model (Oliver, 1980) and the Technology Acceptance Model.

This is consistent with Oliver's Expectation-Confirmation Model within the Technology Acceptance Model (Oliver, 1980) and shows that the use of a system affects satisfaction, which in turn results in loyalty.

H9. Actual use (AU) had a significant direct effect on satisfaction and loyalty (S&L).

H10: The Effect of Hedonic Motivation on Satisfaction and Loyalty – This theory is based on models that integrate hedonic motivation into the Consumer Value Model's Technology Acceptance Model (Holbrook, 1994). It suggests that satisfaction and loyalty are directly influenced by hedonic motivation.

H10. Hedonic Motivation (HM) had a significant direct effect on satisfaction and loyalty (S&L).

Through the integration of these theoretical frameworks, the research endeavors to generate a thorough comprehension of the variables impacting the acceptance and sustained utilization of online meal delivery services amidst a health emergency.

3. Findings

The gender distribution of the participants in the study showed a notable difference, with a higher percentage of females (132 individuals, 58.9%) compared to males (92 individuals, 41.1%). The total ratio of females to males was approximately 3:2.

The participants were enrolled in a variety of courses in Table 1. The most common was Elementary Mathematics Education, with 50 participants (22.3%), followed closely by Preschool Education with 48 participants (21.4%). Special Education Teaching was chosen by 46 participants (20.5%), and both Guidance and Psychological Counseling and Turkish Language and Literature had 40 participants each, accounting for 17.9% of the total in each case. This distribution reflects a diverse academic interest among the participants.

Regarding preferences for food delivery e-commerce platforms, a majority of participants opted for Yemek Sepeti, with 148 individuals accounting for 66.0% of the responses. Getir Yemek was the second most popular choice with 48 participants (21.4%), followed by Trendyol Yemek with 19 participants (8.4%). A smaller portion of the participants, 9 individuals (4.2%), opted for other platforms not listed in the survey. This indicates a strong preference for Yemek Sepeti among the participants for food delivery services.

Table 1. Participants' demographics in the survey

(1) Gender N (%)		**Total (Ratio)**
	Female	132 (58.9)
	Male	92 (41.1)
(2) Course Studying N (%)		
	Elementary Mathematics Education	50 (22.3)
	Preschool Education	48 (21.4)
	Special Education Teaching	46 (20.5)
	Guidance and Psychological Counseling	40 (17.9)
	Turkish Language and Literature	40 (17.9)
(3) Food Delivery e-commerce Platforms		
	Getir Yemek	48 (21.4)
	Trendyol Yemek	19 (8.4)
	Yemek Sepeti	148 (66.0)
	Others	9 (4.2)

The eleven constructs that make up an Integrated TRA and TAM are PSEV, ITU, AU, PS, RC, ND, IQ, CM, PEOU, HM, and S&L. Eleven TPB constructs in total were analyzed in order to evaluate the measurement model. Every item was assigned to a construct, and its factor loadings, Composite Reliability (CR), and Average Variance Extracted (AVE) were evaluated, as indicated in Table 2.

Five items were used to measure the perceived severity construct, yielding an average variance extracted of 0.614 and a composite reliability of 0.887. The items' factor loadings varied from 0.692 to 0.868, suggesting convergent validity and a satisfactory degree of internal consistency. Four items in the intention to use construct had an AVE of 0.674 and a strong composite reliability of 0.891. With factor loadings ranging from 0.678 to 0.923, the construct was measured with good robustness. Four items—with an AVE of 0.697 and a high composite reliability of 0.902—were used to measure actual use. Factor loadings showed a trustworthy assessment of real use, ranging from 0.790 to 0.876. Three items were used to evaluate perceived severity, yielding an AVE of 0.671 and a composite reliability of 0.856. The factor loadings showed a satisfactory perceived severity, ranging from 0.609 to 0.920. Four items were used to measure restaurant credibility; the results showed an AVE of 0.610 and a composite reliability of 0.861. The factor loadings varied between 0.685 and 0.856, suggesting that restaurant credibility can be measured with validity. Four items were used to evaluate navigational design, yielding an AVE of 0.691 and a composite reliability of 0.899. The factor loadings, which ranged from 0.752 to 0.865, showed a trustworthy indicator of the navigational design. Four items were used to measure the item-information quality, and the results showed a strong composite reliability of 0.919 and an AVE of 0.740. The range of factor loadings, which shows a reliable indicator of information quality, is 0.837 to 0.879. Three items were used to measure convenience motivation; the results showed an AVE of 0.703 and a composite reliability of 0.876. With factor loadings ranging from 0.767 to 0.889, the convenience motivation was measured reliably. Four items were used to measure perceived ease of use, yielding an AVE of 0.704 and a high composite reliability of 0.905. Factor loadings ranged from 0.803 to 0.860, indicating a trustworthy indicator of perceived usability. Three items were used to measure hedonic motivation, and the results showed an AVE of 0.546 and a composite reliability of 0.781. The factor loadings fell between 0.654 and 0.853, suggesting that the measure of hedonic motivation is appropriate. Six items were used to measure satisfaction and loyalty, yielding an AVE of 0.618 and a high composite reliability of 0.906. Factor loadings ranged from 0.692 to 0.837, indicating a dependable indicator of the reasons behind satisfaction and loyalty.

The Standardized Root Mean Square Residual (SRMR), which was 0.079, was used to assess the model's fit. In Table 2, this value shows that the model fits the data well, as it is less than the typical cutoff of 0.08 (MacCallum et al., 1996). The model's constructs exhibited satisfactory to excellent reliability and validity, as evidenced by the composite reliability (CR) values, average variance extracted (AVE), and factor loadings. According to Hair et al. (2010), Hair et al. (2010), and Hair et al. (2017), respectively, these values should be above 0.7, above

0.5, and 0.7. Additionally, the structural model fit was found to be satisfactory, boosting confidence in the measurement model's validity.

Table 2. Items, Factor Loadings, Composite Reliability (CR), Standardized Root Mean Square Residual Value (SRMR) of the structural model, Average Variance Extracted (AVE) of a Structural Model

An Integrated TPB and TAM constructs	Items	Factor Loadings	CR	AVE
PSEV	PSEV1	0.868	0.887	0.614
	PSEV2	0.692		
	PSEV3	0.811		
	PSEV4	0.841		
	PSEV5	0.697		
ITU	ITU1	0.767	0.891	0.674
	ITU2	0.892		
	ITU3	0.923		
	ITU4	0.678		
AU	AU1	0.810	0.902	0.697
	AU2	0.790		
	AU3	0.860		
	AU4	0.876		
PS	PS1	0.892	0.856	0.671
	PS2	0.920		
	PS3	0.609		
RC	RC1	0.856	0.861	0.610
	RC2	0.834		
	RC3	0.736		
	RC4	0.685		
ND	ND1	0.843	0.899	0.691
	ND2	0.860		
	ND3	0.865		
	ND4	0.752		
IQ	IQ1	0.856	0.919	0.740
	IQ2	0.869		
	IQ3	0.879		
	IQ4	0.837		
CM	CM1	0.767	0.876	0.703
	CM2	0.855		
	CM3	0.889		
PEOU	PEOU1	0.857	0.905	0.704
	PEOU2	0.803		
	PEOU3	0.860		
	PEOU4	0.833		
HM	HM1	0.695	0.781	0.546
	HM2	0.654		
	HM3	0.853		
S&L	SL1	0.805	0.906	0.618
	SL2	0.837		
	SL3	0.731		
	SL4	0.819		
	SL5	0.821		
	SL6	0.692		
Structural model fit				
SRMR (0.079)				

A correlation analysis was carried out to investigate the connections among different constructs related to user engagement and perception. Table 3 presents the findings, which revealed multiple significant correlations.

Strong positive correlations were found between the Intention to Use (ITU) construct and the Satisfaction and Loyalty (S&L; r = 0.830), Actual Use (AU; r = 0.760), and Perceived Severity (PSEV; r = 0.657) constructs. This suggests that a greater desire to interact with a system or product is positively correlated with higher levels of user satisfaction, loyalty, and actual usage in addition to a greater perceived severity.

Satisfaction and Loyalty (S&L; r = 0.754) and Actual Use (AU) were found to positively correlate, suggesting that actual interaction with the system or product increases user satisfaction and loyalty.

On the other hand, a weak negative correlation was observed between Perceived Ease of Use (PEOU) and Perceived Severity (PSEV; r = -0.145). This suggests that there is a complex relationship between the two variables, with higher self-efficacy variance and lower perceived ease of use. The results indicate that there is a significant positive correlation between PEOU and Restaurant Credibility (RC; r = 0.773). This suggests that the perception of restaurant credibility is greatly influenced by ease of use.

The primary construct that surfaced was Item-Information Quality (IQ), which showed strong positive correlations with Actual Use (AU; r = 0.656), Perceived Ease of Use (PEOU; r = 0.658), and Satisfaction and Loyalty (S&L; r = 0.765). The importance of item-information quality in improving user interaction, perceived ease of use, overall satisfaction, and loyalty is highlighted by this.

Hedonic Motivation (HM) exhibited moderate relationships with multiple constructs. Notable correlations were found with Satisfaction and Loyalty (S&L; r = 0.675) and Perceived Self-Efficacy Variance (PSEV; r = 0.620). These connections imply that self-efficacy perceptions are influenced and user satisfaction and loyalty are promoted by the delight and pleasure experienced during interactions.

Table 3. Matrices of Correlation for Constructs

Constructs	PSEV	ITU	AU	PS	RC	ND	IQ	CM	PEOU	HM	S&L
PSEV	1										
ITU	0.657	1									
AU	0.644	0.760	1								
PS	0.642	0.568	0.487	1							
RC	0.619	0.501	0.419	0.667	1						
ND	0.582	0.553	0.565	0.637	0.630	1					
IQ	0.633	0.645	0.656	0.716	0.676	0.763	1				
CM	0.510	0.606	0.422	0.534	0.585	0.517	0.495	1			
PEOU	-0.145	0.602	0.486	0.547	0.773	0.663	0.658	0.699	1		
HM	0.620	0.646	0.577	0.458	0.401	0.479	0.491	0.410	0.411	1	
S&L	0.672	0.830	0.754	0.659	0.583	0.675	0.765	0.595	0.642	0,675	1

The theories were put to the test in order to evaluate the connections within the suggested structural model. All of the hypotheses were confirmed because the T-values for the structural model were shown to be adequate, despite Hair et al. (2017)'s recommendation that they be either above or below +1.96. Table 4 presents a summary of the results, along with T-values, p-values, and path coefficients. The findings are also discussed below.

Strong support for the hypothesis was shown by the path from Perceived Severity (PSEV) to Intention to Use (ITU) (H1), which showed a significant positive relationship with a path coefficient of 0.657, T-value of 12.194, and p-value of <0.001 (***). This relationship demonstrated the significant influence of perceived severity perceptions on users' intention to interact with the system, accounting for 43.2% of the variance in ITU.

A significant positive relationship was also shown in the transition from Intention to Use (ITU) to Actual Use (AU) (H2), with a path coefficient of 0.760, T-value of 21.010, and p-value of less than 0.001 (***). There is a significant correlation between users' intention and their actual engagement with the system, as evidenced by the relationship that accounted for 57.7% of the variance in AU.

The effects of Perceived Severity (PS), Restaurant Credibility (RC), and Navigational Design (ND) on Item-Information Quality (IQ) were evaluated in Hypotheses H3, H4, and H5. The three paths—PS->IQ (H3), RC->IQ (H4), and ND->IQ (H5)—all displayed statistically significant positive relationships, with path coefficients of 0.302, 0.192, and 0.451, respectively. All of their p-values were less than 0.001 (***), and their corresponding T-values were 4.790, 2.606, and 6.749. Taken together, these factors accounted for 69.0% of the variation in IQ, highlighting the crucial impact of perceived severity, restaurant credibility, and navigational design on the information's perceived quality.

With a path coefficient of 0.699, T-value of 25.691, and p-value of <0.001 (***), the relationship between Convenience Motivation (CM) and Perceived Ease of Use (PEOU) (H6) was found to be strongly supported, explaining 48.8% of the variance in PEOU.

A path coefficient of 0.663, a T-value of 9.114, and a p-value of less than 0.001 (***) further supported the hypothesis connecting Perceived Ease of Use (PEOU) to Navigational Design (ND) (H7). This route accounted for 44.0% of the variation in ND.

Lastly, using hypotheses H8, H9, and H10, the effects of Item-Information Quality (IQ), Actual Use (AU), and Hedonic Motivation (HM) on Satisfaction and Loyalty (S&L) were investigated. With a path coefficient of 0.418 for IQ->S&L, 0.312 for AU->S&L, and 0.290 for HM->S&L, all three paths were statistically significant. All of their p-values were less than 0.001 (***), and their corresponding T-values were 7.799, 5.428, and 5.929. The combined impact of information quality, actual system use, and system enjoyment on user satisfaction and loyalty was highlighted by the fact that these variables accounted for 75.1% of the variance in satisfaction and loyalty. The structural model is illustrated in Figure 2.

Table 4. Hypothesis Testing of the Structural Model

Structural Model	Path Coefficients	T Values	Results	p-value
PSEV-> ITU **(H1)**	0.657	12.194	**SUPPORTED**	0.000 (***)
ITU Explained as %: (43.2)				
ITU->AU **(H2)**	0.760	21.010	**SUPPORTED**	0.000 (***)
AU Explained as %: (57.7)				
PS->IQ **(H3)**	0.302	4.790	**SUPPORTED**	0.000 (***)
RC->IQ **(H4)**	0.192	2.606	**SUPPORTED**	0.000 (***)
ND->IQ **(H5)**	0.451	6.749	**SUPPORTED**	0.000 (***)
IQ Explained as %: (69.0)				
CM->PEOU **(H6)**	0.699	25.691	**SUPPORTED**	0.000 (***)
PEOU Explained as %: (48.8)				
PEOU->ND **(H7)**	0.663	9.114	**SUPPORTED**	0.000 (***)
ND Explained as %: (44.0)				
IQ->S&L **(H8)**	0.418	7.799	**SUPPORTED**	0.000 (***)
AU->S&L **(H9)**	0.312	5.428	**SUPPORTED**	0.000 (***)
HM->S&L **(H10)**	0.290	5.929	**SUPPORTED**	0.000 (***)
Structural Model: S&L Explained as %: (75.1)				

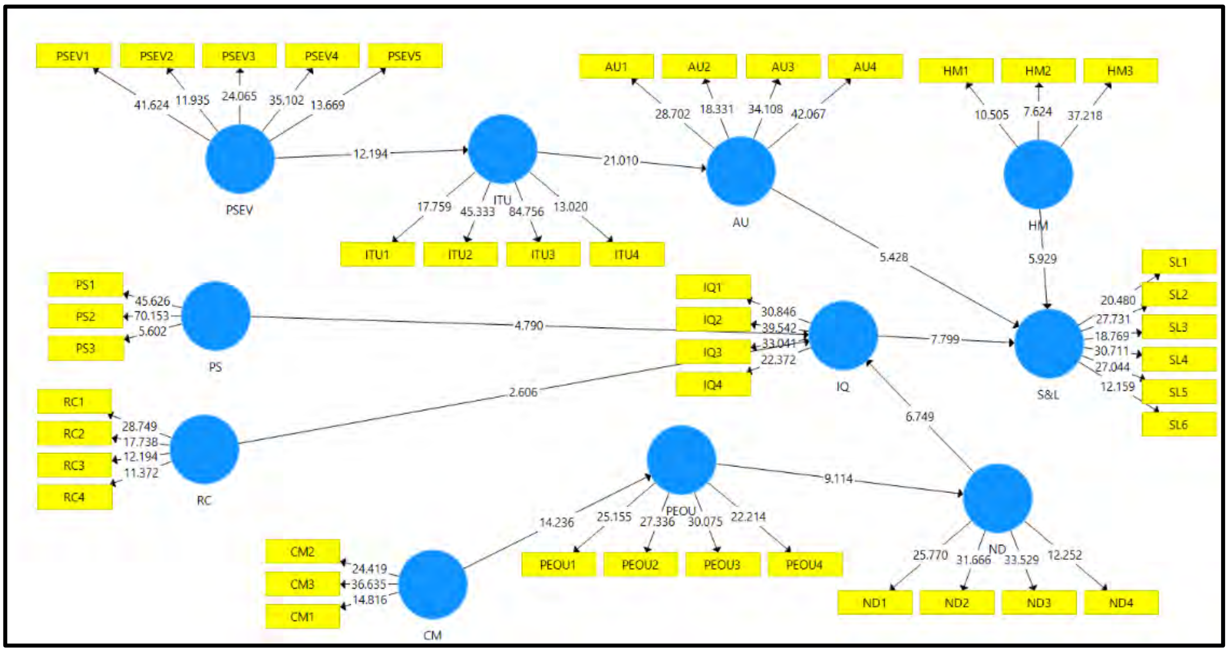

Figure 2. Structural model

4. Conclusion and Discussion

H1 suggests that the perceived severity of COVID-19 (PSEV) has a significant direct effect on intention to use food ordering e-commerce platforms (ITU) among university students in Izmir. This theory is supported by research showing how health concerns influence consumer behavior (Longgang and Ming, 2023); the COVID-19 pandemic has made students in Izmir more concerned about their health and where they can eat safely, and they prefer food delivery services because they perceive COVID-19 as a serious threat. Food delivery platforms should prominently emphasize health and safety measures in their marketing strategies to attract health-conscious boarders. In addition, the use of machine learning algorithms and data mining techniques such as clustering and segmentation can personalize health and safety information based on boarders' behavior and preferences, thereby increasing user engagement. For example, clustering algorithms such as k-means group users based on their level of health awareness, enabling the platform to send personalized safety-related notifications and offers. This finding highlights the importance of a health-conscious marketing strategy. Each platform should highlight the safety measures it has in place and communicate this through personalized notifications and advertisements. Such actions can increase trust and align with students' increased health awareness during and after a pandemic.

H2 showed that intention to use (ITU) significantly influenced actual use (AU) of a food delivery e-commerce platform. This relationship is consistent with the theory of planned behavior (Ajzen, 1991), which shows that in Izmir, as in many other urban areas, high intention to use these platforms leads to actual use. Platforms should implement loyalty programs and personalized promotions to link dormitory students' usage intentions with actual usage. Machine learning algorithms and association rule mining can analyze dorm students' data and create targeted promotions and recommendations to increase the likelihood of intentions turning into actions. Association rule mining, like apriori algorithms, can identify students' frequent purchase patterns, enabling platforms to design targeted loyalty programs and gamified reward systems. Such efforts can bridge the gap between intention and action, as TPB suggests, and enable students to realize their intentions more often. Personalized discounts and gamified rewards are potential solutions to increase engagement.

According to H3, H4 and H5, university students' perceptions of product-information quality (IQ) in Izmir are significantly influenced by price-sales (PS), restaurant reliability (RC) and navigation design (ND). These factors shape how students perceive information quality. Perceived pricing policy significantly influences perceived information and product quality (Venkatesh et al., 2012), restaurant reliability influences perceived information quality (Prasetyo et al., 2021), and user-friendly design enhances perceived information quality (Pillai et al., 2022). Platforms should provide transparent pricing, promote highly rated restaurants, and continuously improve the user interface to increase boarders' perception of information quality. Machine learning algorithms and data mining techniques such as decision trees and regression analysis can be used to optimize pricing strategies and improve user interface design based on boarder feedback and behavioral analysis. Decision tree models can analyze pricing preferences, while A/B testing can optimize UI layouts to enhance user satisfaction. For example, testing variations of navigation menus can reveal which design improves perceived information quality. Platforms should provide a transparent pricing policy and display verified customer reviews to increase credibility and trust. Furthermore, continuous testing of the user interface through A/B testing can improve the navigation experience and the quality of perceived information.

H6 and H7 examined the relationship between convenience motivation (CM), perceived ease of use (PEOU), navigation design (ND) and item-information quality (IQ). Convenience motivated students found these platforms easier to use and associated them with perceived ease of use (PEOU). Intuitive navigation design improves user experience and increases perceived information quality (Longgang & Ming, 2023). Platforms should focus on streamlining the user experience for matrons, reducing the number of steps required to place orders, and ensuring that the app is intuitive and easy to navigate. The use of machine learning algorithms and data mining techniques such as usability testing and A/B testing to analyze user interactions and continuously improve the user interface can increase ease of use and convenience for boarding students. Sentiment analysis using natural language processing (NLP) tools can process app reviews and identify common pain points in navigation. Platforms should regularly monitor user feedback through sentiment analysis, identify UI pain points and take proactive steps to address them. For example, the checkout process could be streamlined to improve overall convenience and perceived ease of use.

H8 suggests that information quality (IQ) has a direct impact on satisfaction and loyalty (S&L). Quality information fosters trust and increases satisfaction and loyalty (Venkatesh et al. To build and maintain the trust of dormitory students, constantly updated and accurate information about menus, prices and delivery times should be provided. Data mining techniques such as machine learning algorithms, text mining and sentiment analysis can help ensure the accuracy and relevance of information by dynamically updating content based on resident interaction and external factors. The platform should use a real-time data pipeline using Apache Kafka to dynamically update content based on external factors and user interactions. Dynamic systems that utilize real-time updates can further increase student loyalty by ensuring that information remains accurate and up-to-date.

According to H9, actual usage (AU) has a significant impact on satisfaction and loyalty (S&L) as positive usage experiences increase satisfaction and loyalty (Pal et al., 2022). Ensuring reliable and timely delivery, accurate order processing and prompt customer service increase satisfaction and loyalty among boarding customers. Machine learning algorithms and data mining techniques such as predictive analytics and logistics optimization can optimize delivery routes, predict order processing times, and improve customer service responsiveness through chatbots and predictive analytics. Predictive analytics can estimate delivery times and suggest adjustments to improve operational efficiency. Furthermore, the integration of APIs such as Google Maps can improve the optimization of delivery routes.

H10 suggested that hedonic motivation (HM) has a significant impact on satisfaction and loyalty (S&L) and that enjoyable experiences increase satisfaction and loyalty (Prasetyo et al., 2021). Platforms should include features that enhance customers' enjoyment of the ordering experience, such as gamification, personalized recommendations, and engaging promotions. Machine learning algorithms and data mining techniques, such as collaborative filtering and recommendation systems, can personalize the user experience and make the process more enjoyable for residential customers by recommending items based on past behavior and preferences. A recommendation system using collaborative filtering provides students with personalized meal suggestions, while gamification features such as leaderboards and rewards for frequent ordering add to the fun.

.The results of this study reveal the complex dynamics affecting university students' use of food delivery e-commerce platforms in Izmir: The strong correlation between perception of COVID-19 severity and intention to use these platforms points to students' health awareness during the pandemic, highlighting the increased awareness of students' health during a pandemic. This realization underscores the need to focus on health and safety measures even after a pandemic. Furthermore, the significant impact of price, restaurant reliability, and navigation design on perceived information quality highlights key factors that platforms need to address to meet user expectations. Extending these insights to other cities and countries would provide a more comprehensive understanding of students' behavior in different contexts. The interplay between convenience, ease of use and navigation design reveals the importance of a smooth and intuitive user experience. These insights emphasize the need for food delivery platforms to constantly innovate and adapt to users' changing tastes and interests.

The findings have several policy implications for Izmir's food delivery e-commerce platform and local governments. Platforms should focus on improving perceived information quality and navigation design to increase user satisfaction and loyalty. In addition, emphasizing the health and safety aspects of using food delivery services can further increase user engagement, especially in the context of ongoing health concerns such as the COVID-19 pandemic. For local policymakers, supporting and regulating these platforms and ensuring high service standards can contribute to the overall satisfaction and well-being of the student population.

In conclusion, this study provides valuable insights into Turkish university students' intentions and behaviors towards food ordering e-commerce platforms. The findings will inform companies and platforms on how to adapt to the specific needs of Izmir's diverse student population, foster innovation, and respond to changing user preferences.

References

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

Ali, S., Khalid, N., Javed, H. M. U., and Islam, D. M. Z. (2020). Consumer adoption of online food delivery ordering (OFDO) services in Pakistan: The impact of the COVID-19 pandemic situation. *Journal of Open Innovation: Technology, Market, and Complexity*, *7*(1), 10. https://doi.org/10.3390/joitmc7010010

Bandura, A. (1986). *Social foundations of thought and action: A social cognitive theory*. Englewood Cliffs, NJ: Prentice-Hall.

Biswas, A., and Verma, R. K. (2022). Augmenting service quality dimensions: Mediation of image in the Indian restaurant industry. *Journal of Foodservice Business Research, 26*(3), 496-527. https://doi.org/10.1080/15378020.2022.2027198

Bordelon, B. M., Lee, Y. M. and Chen, H. (2021). Exploring the impacts of FDA temporary food labeling flexibility among the food allergy community during the Covid-19 pandemic. *Journal of Foodservice Business Research, 26*(2), 276-297. https://doi.org/ 10.1080/15378020.2021.2015228

Byrd, K. Fan, A., Her, E., Liu, Y., Leitch, S., and Almanza, B. (2021). Restaurant patronage during the COVID-19 pandemic and the protection motivation theory: influence of consumers' socio-demographic, situational, and psychographic factors. *Journal of Foodservice Business Research, 26*(2), 247-275. https://doi.org/10.1080/15378020.2021.2006036

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

DeLone, W. H., and McLean, E. R. (1992). Information systems success: The quest for the dependent variable. *Information Systems Research, 3*(1), 60-95. https://doi.org/10.1287/isre.3.1.60

Gefen, D., Karahanna, E., and 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

Hair, J. F., Black, W.C., Babin, B. J., and Anderson, R. E. (2010), *Multivariate data analysis: A global perspective* (7th edition). Pearson Education, Upper Saddle River.

Hair Jr, J. F., Sarstedt, M., Ringle, C. M., and Gudergan, S. P. (2017). *Advanced issues in partial least squares structural equation modelling.* Sage publications Inc.

Herrera, C., and Young, C. A. (2022). Revenue management in restaurants: The role of customers' suspicion of price increases. *Journal of Foodservice Business Research, 26*(3), 425-449. https://doi.org/10.1080/15378020.2022.2027200

Holbrook, M. B. (1994). The nature of customer value: An axiology of services in the consumption experience. *Service Quality: New Directions in Theory and Practice*, 21-71.

Kim, D. J., Ferrin, D. L., and Rao, H. R. (2009). Trust and satisfaction, two stepping stones for successful e-commerce relationships: A longitudinal exploration. *Information Systems Research, 20*(2), 237-257. https://doi.org/10.1287/isre.1080.0188

Longgang, G., and Ming, C. W. (2023). An Empirical Study on the Perceive Severity, Perceive Ease of Use and Information Quality on the SME' Businesses in China. *Journal of Digitainability, Realism and Mastery (DREAM), 2*(10), 1-9. https://doi.org/10.56982/dream.v2i10.158

MacCallum, R. C., Browne, M. W., and Sugawara, H. M. (1996). Power analysis and determination of sample size for covariance structure modeling. *Psychological Methods, 1*(2), 130-149. https://doi.org/10.1037/1082-989X.1.2.130

Oliver, R. L. (1980). A cognitive model of the antecedents and consequences of satisfaction decisions. *Journal of Marketing Research, 17*(4), 460-469. https://doi.org/10.1177/002224378001700405

Pal, D., Funilkul, S., Eamsinvattana, W., and Siyal, S. (2022). Using online food delivery applications during the COVID-19 lockdown period: What drives University Students' satisfaction and loyalty? *Journal of Foodservice Business Research*, 25(5), 561-605. https://doi.org/10.1080/15378020.2021.1964419

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://www.jstor.org/stable/27751067

Pillai, S. G., Kim, W. G., Haldorai, K., and Kim, H. S. (2022). Online food delivery services and consumers' purchase intention: integration of theory of planned behavior, theory of perceived risk, and the elaboration likelihood model. *International journal of hospitality management, 105*, 103275. https://doi.org/10.1016/j.ijhm.2022.103275

Prasetyo, Y.T., Tanto, H., Mariyanto, M., Hanjaya, C., Young, M. N., Persada, S. F., Miraja, B. A., and Redi, A. A. N. P. (2021). Factors Affecting Customer Satisfaction and Loyalty in Online Food Delivery Service during COVID-19 Pandemic in A Developing Country: An Extended Theory of Planned Behavior. *Journal Open Innovation Technology Market and Complexity, 7*(1), 76. https://doi.org/10.3390/joitmc7010076

Roe, S. J., and Smith, R. P. (2021). Asking for help: Restaurant crowdfunding during COVID-19. *Journal of Foodservice Business Research, 26*(2), 164-185. https://doi.org/ 10.1080/15378020.2021.2006038

Rogers, M. E. (2003). *Diffusion of Innovations*. 5th Edition, Free Pass, New York.

Rosenstock, I. M. (1974). Historical origins of the health belief model. *Health Education Monographs 2*(4), 328-335. https://doi.org/10.1177/109019817400200403

Statistica.Com.(2023), Retail Delivery – Turkey, https://www.statista.com/outlook/dmo/online-food-delivery/turkey#:~:text=The%20Online%20Food%20Delivery%20market,37.1%25%20is%20expected%20in%202024. Retrieved on 28.12.2023

Taylor, S., and Todd, P. A. (1995). Understanding information technology usage: A test of competing models. *Information Systems Research, 6*(2), 144-176. https://doi.org/10.1287/isre.6.2.144

Turban, E., Outland, J., King, D., Lee, J. K., and Liang, T. P. (2017). *Electronic commerce 2018: A managerial and social networks perspective*. Springer.

Venkatesh, V., Morris, M. G., Davis, G. B., and 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., and 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., Thong, J. Y., and 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, W., and Benbasat, I. (2005). Trust in and adoption of online recommendation agents. *Journal of the Association for Information Systems, 6*(3), 72-101. https://doi.org/10.17705/1jais.00065

Zapata-Cuervo, N., Montes-Guerra, M. I., and Jeong, M. (2021). How do restaurants respond to the COVID-19 pandemic? Lessons from Colombian restauranteurs and their survival strategies. *Journal of Foodservice Business Research, 26*(2), 186-207. https://doi.org/10.1080/15378020.2021.2006037

Appendix A. Questionnaire Form

- Gender N (%)
- Course Studying N (%)
- Food Delivery e-commerce Platforms usage

PSEV (Perceived Severity)

- PSEV1: I understand social distancing regulations, so I use food delivery e-commerce instead of eating or buying my own food.
- PSEV2: I am afraid to eat in restaurants due to the COVID-19 pandemic.
- PSEV3: I find food delivery e-commerce helpful in satisfying my desire to eat when COVID-19 is prevalent.
- PSEV4: I think food delivery e-commerce is a solution for the limited number of seats in restaurants due to social distancing restrictions.
- PSEV5: Food delivery e-commerce helps me eat meals that I cannot cook when I am too lazy to eat out.

ITU (Intention to Use)

- ITU 1: I plan to use food delivery e-commerce in the future.
- ITU2: I will always use food delivery e-commerce in my daily life.
- ITU3: I intend to use food delivery e-commerce often in the future.
- ITU4: I decided to use food delivery e-commerce to buy food and drinks next time.

AU (Actual Use)

- AU1: I always use food delivery e-commerce’s app to buy food.
- AU2: I prefer to use food delivery e-commerce 's app instead of the store's delivery service.
- AU3: I always check the available stores.
- AU4: I always check announcements and promotions.

PS (Price to Sale)

- PS1: Food delivery e-commerce implementation gives me peace of mind as there are steps to protect the payment instrument before payment is made.
- PS2: Both users and drivers can reduce risk by taking a step to check before using.

- PS3: I think Food delivery e-commerce providers should not give personal information to other organizations.

RC (Restaurant Credibility)
- RC1: I think that the restaurant's score on the food delivery e-commerce app is a good basis for ordering decisions.
- RC2: I am also interested in the number of reviews about the restaurant when ordering.
- RC3: I like to shop from popular and well-known restaurants.
- RC4: I think that the number of restaurant outlets influences my ordering.

ND (Navigational Design)
- ND1: I find the navigation bar in food delivery e-commerce useful.
- ND2: I can easily jump to other pages and back in the food delivery e-commerce app.
- ND3: I find the dynamic filter helps me find the restaurant or cuisine I am looking for.
- ND4: I think the keyword search in the food delivery e-commerce app saves me a lot of time.

IQ (Item-Information Quality)
- IQ1: Food delivery e-commerce provides me with up-to-date information about restaurants, food and discounts.
- IQ2: I enjoy using food delivery e-commerce because it provides reliable information.
- IQ3: I think food delivery e-commerce gives me exactly the information I need.
- IQ4: I think the information in the food delivery e-commerce app is in a convenient format.

CM (Convenience Motivation)
- CM1: I can order anytime, anywhere.
- CM2: I feel that using food delivery e-commerce reduces the need to travel to buy food and drinks.
- CM3: I feel that using food delivery e-commerce saves me more time than buying food and drinks in person.

PEOU (Perceived Ease of Use)
- PEOU1: I can easily find what I need in the food delivery e-commerce app.
- PEOU2: Food delivery e-commerce has buttons that provide information.
- PEOU3: I can complete tasks quickly.
- PEOU4: I feel that the Food delivery e-commerce app is well designed, positioned and organized.

HM (Hedonic Motivation)
- HM1: I would not use food delivery e-commerce just to meet my basic needs.
- HM2: Food delivery e-commerce has many minimum purchase amounts and promotions, so using food delivery e-commerce is more economical than buying them yourself.
- HM3: I enjoy using food delivery e-commerce to give someone food or drink as a gift.

S&L (Satisfaction and Loyalty)
- SL1: I am satisfied with food delivery e-commerce’s method of operation.
- SL2: Overall, I am satisfied with food delivery e-commerce 's service.
- SL3: I always sign up for food delivery e-commerce promotions.
- SL4: I would like to use food delivery e-commerce in the future.
- SL5: I would recommend food delivery e-commerce to others.
- SL6: I will share my experiences of using food delivery e-commerce with the public.