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Research Article

Factors influencing customer satisfaction and loyalty in Artificial Intelligence (AI)-driven food delivery systems during and post COVID-19

COVİD-19 süresince ve sonrasında yapay zekâ destekli yemek teslimat sistemlerinde müşteri memnuniyeti ve sadakatini etkileyen faktörler

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Abstract

The research aims to determine how various factors influence customer satisfaction and loyalty (CS&L) in AI-driven food delivery systems during and after COVID-19. Two hundred ninety-four participants were given a 32-item questionnaire, and the data were analysed using multiple regression analysis and quantitative research methods. Numerous factors were examined in this inquiry, such as price reduction, promotion benefits, information quality, hedonic motivation, safety packaging, and perceived severity. The research illustrates how the pandemic affected consumer behaviour, with an adjusted R^2 value of 0.715 during the pandemic and 0.489 in the post-pandemic period. It also concludes that hedonic motivation and information quality are two essential elements influencing consumer satisfaction and loyalty. The research seeks to enhance the post-pandemic delivery of AI-supported services and help provide recommendations for developing AI systems for food delivery services with a better understanding of consumer motivation for AI-based food delivery services.

Keywords: AI-Driven Food Delivery Systems, COVID-19, Multiple Regression Analysis, Customer Satisfaction and Loyalty

Jel Codes: L81, M31, D12

Öz

Bu araştırma, COVİD-19 esnasında ve sonrasında, yapay zekâ destekli yemek dağıtım sistemlerinin farklı boyutlarının müşteri tatmini ve bağlılığı üzerine olan etkilerini değerlendirmeyi amaçlamaktadır. 294 katılımcıya 32 soru yöneltilmiş ve buradan elde edilen verilere, nicel araştırma yöntemi ve çoklu regresyon analizi gerçekleştirilmiştir. Bu analizde fiyat indirimi, promosyon faydası, bilgi kalitesi, hedonik motivasyon, güvenli ambalajlama ve algılanan şiddet gibi faktörler incelenmiştir. Pandemi sırasında düzeltilmiş R^2 değeri 0,715, pandemi sonrası dönemde ise 0,489 olan bu çalışma ile salgının tüketici davranışlarını nasıl etkilediği ortaya konmaktadır. Ayrıca, bilgi kalitesi ve hedonik motivasyonun müşteri memnuniyeti ve sadakati (MMS) üzerindeki önemli iki etken olduğu sonucuna varılmıştır. Bu araştırma, salgın sonrası dönemde yapay zekâ destekli hizmet sunumunun geliştirilerek yapay zekâ tabanlı yemek dağıtım hizmetlerine yönelik tüketici motivasyonunun daha iyi anlaşılmasını sağlamayı hedeflemektedir. Bu araştırma, yemek teslimat sistemleri için yapay zekâ sistemlerinin geliştirilmesine yönelik bazı öneriler sunmaktadır.

Anahtar Kelimeler: Yapay Zekâ Destekli Yemek Teslimat Sistemleri, COVİD-19, Çoklu Regresyon Analizi, Müşteri Memnuniyeti ve Sadakati

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Introduction

Rapid developments in AI in the service sector have significantly transformed the food distribution system, especially during the COVID-19 pandemic, which has shifted consumer behaviour towards more digital interactions. Moreover, AI technologies are important in addressing challenges such as demand forecasting, inventory management, and delivery optimisation, thereby contributing to food distribution operations' overall sustainability and efficiency (Tsolakis, Schumacher, Dora & Kumar, 2022). Food distribution platforms can use AI-driven solutions to improve competitiveness and customer retention and adapt to evolving consumer preferences and behaviours (Weiler & Gilitwala, 2023). Therefore, research on the impact of AI on food distribution systems is essential to understand the potential impact of AI technology on the food distribution industry, customer satisfaction and operational efficiency.

The AI-driven food delivery industry has experienced a notable upsurge in usage due to the pandemic. Numerous studies have been conducted on the factors that affect CS&L in AI-driven food delivery systems during and after the COVID-19 pandemic. Some researchers, such as Suhartanto, Ali, Tan, Sjahroeddin and Kusdibyo (2018) and Saad (2020), have shown how crucial factors affecting CS&L in online meal delivery services include e-service quality, food quality, delivery time, and the condition of the food delivered. Additionally, the ban on single-use plastics has brought attention to the packaging used in AI-driven food delivery platforms, emphasising the need for sustainable and safe packaging to ensure CS&L (Li, Chen, Liu, Zhang & Mu, 2021). These findings highlight the importance of addressing these factors in the context of AI-powered food delivery websites during and after the pandemic to improve CS&L. Overall, these researches emphasise how complex the variables affect CS&L in AI-driven food delivery websites both before and after the pandemic. That highlights how important it is to consider the food quality, the e-service, the packaging, the delivery time, and sustainability in the rapidly evolving AI-driven food delivery market to ensure CS&L.

AI-driven food delivery systems leverage machine learning algorithms to personalise user experiences, optimise delivery logistics, and enhance customer satisfaction through more innovative recommendation systems and interactive interfaces (Shekhar & Vartika, 2022). The integration of chatbots and virtual assistants further streamlines the order placement process and improves overall service efficiency (Shekhar & Vartika, 2022). The emergence of AI-driven food delivery services in Türkiye reflects a broader trend of technological innovation intersecting with consumer behaviour and cultural preferences (Bozdag & Durmus, 2023). With a diverse population of over 13 million people aged in their 20s and a strategic location at the crossroads of Europe and Asia, Türkiye presents a unique market for the evolution of food delivery systems (Baris & Yilmaz, 2022). The country's transition from traditional phone-based ordering to sophisticated online platforms has been accelerated by AI technologies, revolutionising how restaurants, consumers, and delivery services interact within the food industry. In the context of Türkiye's rapidly growing e-commerce sector, AI-driven food delivery services have gained significant traction, particularly in urban centres like Istanbul, Ankara, and Izmir, where convenience and speed are paramount for consumers (Baris & Yilmaz, 2022). Baris and Yilmaz (2022) also stated that the thriving start-up ecosystem in Türkiye, with Istanbul emerging as a hub for tech innovation, has further catalysed the development and adoption of AI-driven solutions in various sectors, including food delivery. The country's GDP per capita, high internet access rates, and smartphone penetration levels underscore the population's strong digital engagement, driving the expansion of online services like food delivery in developing countries (Saad, 2020). Despite the rapid growth and acceptance of AI-driven food delivery services in Türkiye, several challenges persist, including privacy concerns, data security issues, and intense market competition (Baglar, 2020). However, these challenges are accompanied by vast opportunities, as the increasing penetration of smartphones and the internet, coupled with Türkiye's rich culinary heritage, create fertile ground for the expansion of AI-driven food delivery services. The country's evolving socio-economic landscape, technological progress, and strong economy position it as a key player in the region's development (Kumar, Rawat, Mohd & Husain, 2021). In conclusion, AI-driven food delivery systems in Türkiye represent a dynamic sector that continues to evolve, offering enhanced convenience, variety, and personalisation to consumers while creating new opportunities for businesses and delivery personnel (Kumar et al., 2021). Embracing the challenges and opportunities presented by AI technology will be crucial for stakeholders in Türkiye's food delivery ecosystem as they navigate the future of this exciting industry (Shekhar & Vartika, 2022). Developing AI-powered meal delivery services in developing nations indicates a more significant movement toward technological innovation and digitalisation (Lezoche, Hernandez, Diaz, Panetto & Kacprzyk, 2020). According to Sujata, Mukul, and Hasandeep (2019), this change is revolutionising the food delivery industry and paving the way for developing countries to assume a key role in the global digital economy. All parties involved in this market must embrace AI technology's opportunities and challenges as it grows and changes (Pigatto, Machado, Negreti & Machado, 2017). The development of AI-driven food delivery services in Türkiye is an interesting sample of how technology can transform established industries and provides insightful information for other markets considering a digital transformation of a similar kind.

While several studies have explored the broad application of AI in improving service delivery, a detailed understanding of how AI capabilities will specifically impact CS&L during and after a pandemic is lacking. In addition, previous studies have explored the impact of factors such as price reduction, promotion benefits, information quality, hedonic motivation, and self-packaging on consumer behaviour during the pandemic. There is a lack of research that specifically examines the influence of perceived severity from COVID-19 alongside price reduction, information quality, and hedonic motivation in Türkiye. Most existing studies offer generalised insights without addressing the impact of AI-driven components such as real-time monitoring, personalised recommendations, and automated customer interaction. The study investigates the changes in AI-driven food delivery systems in the Turkish market, utilising empirical data collected during and after the pandemic. It measures price reduction, information quality, and hedonic motivation at both time points, while promotional effectiveness and safe packaging were only analysed during the pandemic. Additionally, the study assesses perceived severity following the pandemic.

The study investigates changes in AI-based food delivery systems in the Turkish market using empirical data collected during and after the pandemic. Precisely, factors such as price discounting, information quality and hedonic motives are measured at both time points, while promotional effectiveness and safe packaging are analysed only during the pandemic period. Furthermore, the study also assesses perceived severity after the pandemic. This study seeks to fill this gap by providing empirical evidence from the Turkish market that can serve as a model for other regions with similar digital dynamics. This study will focus on the AI-driven food delivery system in Türkiye, which is experiencing rapid technology adoption in the consumer market. This study aims to explore the specific impact of AI capabilities on CS&L. This research contributes to the theoretical and practical understanding of the role of AI in improving customer engagement and retention in the digital economy. By examining essential factors such as price reduction, information quality and hedonic motivation measured during and after the pandemic, as well as promotion benefits and safe packaging assessed only during the pandemic and perceived severity assessed only after the pandemic, this study provides insights into how these factors contribute to building customer loyalty and satisfaction in a post-pandemic world.

Theoretical background and hypotheses development

The effective adoption of AI in this industry demonstrates the potential of developing countries to be global leaders in technological innovation, providing lessons and insights on the advantages and difficulties of this kind of digital transformation for global markets (Pigatto et al., 2017). According to Annosi, Brunetta, Capo and Heideveld (2020), this evolution is changing the food delivery sector and playing a significant role in the emerging role of developing nations in the global digital economy. The AI-driven revolution in the food delivery industry in developing nations reflects the country's wider adoption of digital innovation and technological advancement (Prasetyo et al., 2021). Prasetyo et al. (2021) claim that AI's influence on the food delivery market in developing nations goes beyond improved logistics and tailored client experiences. It is also essential for strategic decision-making and market analytics. Businesses can use big data to forecast consumer preferences, market trends, and potential growth areas (Memon, Pawase, Pavase & Soomro, 2021).

The theoretical underpinnings of this study are based on external variables derived from the Theory of Planned Behaviour (TPB) (Fishbein & Ajzen, 1975), which provides a basis for predicting and explaining individuals' intentions and actual use of various technologies in different domains on digital platforms. These are price reduction (PR), promotion benefits (PROB), information quality (IQ), hedonic motivation (HM), safety packaging (SP), perceived severity (PS), customer loyalty and satisfaction (Prasetyo et al., 2021). Price reduction refers to lowering the cost of a product or service offered to customers. Promotion benefits include customers' benefits and rewards as part of promotional activities (Wieseke, Alavi & Habel, 2014). Information quality refers to customer information's accuracy, reliability and usefulness (Jaiswal, Niraj, & Venugopal, 2010). Hedonic motivation represents the emotional and experiential aspects that drive customer behaviour (Palmatier, Scheer & Steenkamp, 2007). Safety packaging involves products' safe and protective packaging (Haruna, Kaur & Tahira, 2017). Perceived severity refers to the extent to which customers perceive the seriousness of a situation, such as a pandemic or problem (Palmatier et al., 2007). Within this theory, customers' attitudes towards AI-based food delivery services have been demonstrated using these factors (Prasetyo et al., 2021). Attitudes towards behaviour express the degree to which an individual evaluates a particular behaviour positively or negatively, affecting the likelihood of performing that behaviour. Perceived behavioural control reflects an individual's perception of the ease or difficulty of performing a behaviour and encompasses factors such as resources, skills and situational constraints that may facilitate or hinder the performance of the behaviour. Finally, 'intention' is a motivational factor that indicates the extent to which an individual is willing or plans to exert effort to perform a behaviour and is a direct predictor of actual behaviour (Fishbein & Ajzen, 1975). These factors are important in shaping customers' perceptions and experiences, ultimately influencing their satisfaction and loyalty towards the service. These factors are important in food delivery services, especially during and after COVID-19. The literature has studied these factors to understand their impact on customer satisfaction and loyalty. Price discounting (PR) is an important factor during the COVID-19 pandemic, and studies show that perceived price fairness contributes to customer satisfaction and loyalty (Anis, Iqbal, Nazir & Khalid, 2022). Promotional benefits (PROB) and Hedonic motivation (HM) are important in online food delivery services during the pandemic, playing a key role in influencing customer satisfaction and loyalty through factors such as convenience incentives and secure packaging (Carandang & Apritado, 2022). Information quality (IQ) has been highlighted as an important factor influencing customer satisfaction and loyalty, especially in providing accurate and reliable information during the pandemic (Anis et al., 2022). The importance of secure packaging (SP) has increased during pandemic periods, and studies emphasise its role in increasing customer satisfaction and loyalty by ensuring the safety and quality of goods delivered (Palmatier et al., 2007). Perceived severity (PS) is an important factor during the COVID-19 pandemic, influencing customers' perceptions of the safety and reliability of food delivery services (Carandang & Apritado, 2022). The relationship between customer satisfaction, loyalty and various external factors is provided, including the impact of the pandemic on customer behaviour. Kumar et al. (2021) explored the potential of AI and machine learning in the food industry, which can affect customer satisfaction and loyalty in food delivery systems. Baber (2021) suggested that the effectiveness of the pandemic screening system has a positive impact on brand image and customer satisfaction, while Naz, Alshaabani, Rudnak & Magda (2021) found that customer loyalty is positively influenced by service quality and service quality in Indonesia is considered an important antecedent of loyalty, Warden et al. (2020) addressed the promise, progress, and challenges of leveraging AI technology in healthcare, which can have implications for customer satisfaction and loyalty in the healthcare and food delivery sectors. Understanding how these factors interact and influence customer behaviour during and after a pandemic is crucial for businesses to effectively adapt their services and maintain customer satisfaction and loyalty in a rapidly changing environment.

Several researches have concentrated on elements impacting consumers' decisions to use AI-driven food delivery websites during the pandemic. Studies such as Chang and Meyerhoefer (2020) and Alaimo, Fiore, and Galati (2020) delved into the demand for AI-driven food shopping services and the changing consumer behaviour in Italy during the pandemic, highlighting the evolving nature of consumer preferences and behaviours in the context of AI-driven food delivery. Zhong and Moon (2020) explored the drivers of customer satisfaction, loyalty, and happiness in Chinese fast-food outlets, including perceived price, service quality, food quality, and physical environment quality, focusing on the moderating role of gender. The impact of the pandemic on consumers' intention to use online meal delivery services was highlighted in Hong, Choi, Choi and Joung's (2021) investigation of the factors influencing this intention. Amin, Arefin, Alam, Ahammad and Hoque (2021) emphasised the need for a comprehensive framework to capture consumer adoption behaviour by extending the Theory of Planned Behaviour to explain the use of mobile food delivery applications during the pandemic. Similarly, using data from a case study in Bangkok, Thailand, Muangmee, Kot, Meekaewkunchorn, Kassakorn, and Khalid (2021) investigated the factors influencing the behavioural intention of using AI-driven food delivery apps during the pandemic. Chanpariyavatevong et al. (2021) combined Bayesian network and structural equation modelling to predict airline passenger loyalty and propose feasible action plans and regulations to increase customer loyalty. Prasetyo et al. (2021) also found that hedonic motivation, price, information quality and promotion significantly influenced customer satisfaction and loyalty in online food delivery services. This highlights the importance of factors beyond purely utilitarian aspects in shaping customer perceptions. Jun, Yoon, Lee and Lee (2021) found that users' ease of use had no distinct impact on their choice to use AI-driven meal delivery websites during the pandemic. Anser et al. (2021) also emphasised the relationship between Information & Communication Technologies (ICT) adoption and governance and food security in West Africa, pointing out that the difficulties associated with poor governance and inadequate ICT infrastructure make policy effects elusive. Chan and Gao (2021) also emphasised the need for up-to-date quality measurement of AI-driven food delivery. Mustapha, Man, Shah, Kamaruzzaman and Tafida (2022) also explored the mediating role of motivation in the relationships between awareness, accessibility, perceived organisational support, and adoption of internet and communication technologies among extension agents in Nigeria, focusing on the agricultural sector. Maingi and Obonyo (2022) investigated the digitalisation of service delivery in fast-food restaurants in Nairobi, Kenya, as the pandemic recovery strategy. Rai (2022) discussed the problems, obstacles, and future directions for developing citizen-centric e-governance in Nepal, highlighting the importance of citizen-centric approaches.-Carandang and Apritado (2022) examined convenience motive, privacy and safety, perceived severity, price reduction, and safe packaging. They assessed customer intentions to use AI-driven food delivery services related to various factors such as promotional benefits. These researches detail the factors influencing consumers' decisions to use online food delivery services during the pandemic, paying special attention to incentives, governance interactions, quality assessment, user satisfaction, and digital service delivery.

Numerous studies have focused on the factors influencing consumers' choices to use AI-powered food delivery platforms after the pandemic. Koay, Cheah and Chang (2022) found that quality dimensions of online food delivery services, such as assurance, food quality and hygiene maintenance, reliability, safety, and system functioning, contribute to customer satisfaction and loyalty and suggest that they significantly contribute to customer satisfaction and loyalty. This underlines the multidimensional nature of service quality that affects customer perceptions. Furthermore, Jati, Nuryakin, and Handayani (2022) investigated the relationship between service innovation, service delivery systems, customer satisfaction and loyalty. The results showed that service innovation and delivery systems significantly impact customer satisfaction, influencing loyalty. This underlines the interconnectedness of various factors in the formation of customer loyalty. Wilson and Goldie (2022) attempted to assess the relationship between service quality and visitor satisfaction, affecting customer loyalty and positive word-of-mouth communication. Tsolakis et al. (2022) discussed the implementation of AI and blockchain in supply chains, which can impact customer satisfaction and loyalty through improved service quality and efficiency. Els and Bisschoff (2023) built a post-COVID model to measure the brand loyalty of bank customers. Weiler and Gilitwala (2023) emphasised that perceived convenience, time-saving, and price-saving benefits significantly influence the intention to use online food delivery services after a pandemic. This suggests that convenience and cost-effectiveness are important in driving customer behaviour in the food delivery industry.

These studies thoroughly grasp how consumer behaviour changed during the pandemic and what factors affected the uptake and use of AI-driven food delivery services. In addition, several researches have focused on how the pandemic has affected consumer preferences and behaviour. For instance, Mahmood et al. (2022) investigated restaurant diners' switching behaviour during the pandemic, highlighting the role of protection motivation theory in understanding consumer decision-making. Gavilan, Balderas-Cejudo, Fernandez-Lores and Martinez-Navarro (2021) focused on innovation in AI-driven food delivery, drawing insights from the pandemic to understand the evolving landscape of food delivery services. These studies underscore the dynamic nature of consumer behaviour and the need for businesses to adapt to changing preferences and circumstances. Studies conducted on AI-driven food delivery platforms both during and after the pandemic have yielded important new information about the variables affecting consumer behaviour, the pandemic's effects on service demand, and how AI-driven food delivery services are changing to meet the demands of their customers.

The following studies can be utilised to support the hypotheses during and after the pandemic period. Here are the research hypotheses from H1d (during) to H6a (after).

Previous research by Han and Ryu (2009) has shown that price sensitivity and affordability play an important role in shaping user perceptions and behaviour, especially during economic instability.

H1d (during): *Price reduction (PR) in AI-driven food delivery services positively affects CS&L.*

H1a (after): *Price reduction (PR) in AI-driven food delivery services positively affects CS&L.*

Previous research by Lin and Sun (2009) has shown that promotional activities and offers can increase users' engagement and satisfaction with technology services, increasing acceptance and loyalty.

H2d (during): *Promotion benefits (PROB) in AI-driven food delivery services positively affect CS&L.*

H2a (after): *Promotion benefits (PROB) in AI-driven food delivery services positively affect CS&L.*

Research by Aras and Zaidi (2017) has shown that the quality and reliability of information provided to users significantly impacts their trust and satisfaction with technology platforms.

H3d (during): *Information quality (IQ) in AI-driven food delivery services positively affects CS&L.*

H3a (after): *Information quality (IQ) in AI-driven food delivery services positively affects CS&L.*

Research by Cheong and Park (2005) emphasises the importance of hedonic factors such as entertainment in increasing user engagement and loyalty towards technology services.

H4d (during): *Hedonic motivation (HM) in AI-driven food delivery services positively affects CS&L.*

H4a (after): *Hedonic motivation (HM) in AI-driven food delivery services positively affects CS&L.*

Research by Haruna et al. (2017) has shown that safe and secure packaging of products improves user experience and loyalty by increasing user confidence, satisfaction and overall service quality.

H5d (during): *Safe packaging (SP) in AI-driven food delivery services positively affects CS&L.*

H5a (after): *Safe packaging (SP) in AI-driven food delivery services positively affects CS&L.*

Understanding how users perceive the severity of external factors such as the global health crisis can provide insights into their decision-making processes and interactions with technology platforms (Devaraj, Fan, & Kohli, 2002).

H6d (during): *Perceived severity (PS) in AI-driven food delivery services positively affects CS&L.*

H6a (after): *Perceived severity (PS) in AI-driven food delivery services positively affects CS&L.*

By testing these hypotheses, researchers can gain valuable insights into the factors driving user acceptance, satisfaction, and loyalty towards technology-based services during and after the COVID-19 pandemic.

Methodology

The research used a quantitative design to examine the variables affecting consumer loyalty and satisfaction in AI-driven food delivery services before and after the pandemic. A structured online questionnaire was used to collect data from Turkish consumers of online food delivery services. The data were collected through Google Forms and consisted of 32 items, including a seven-point Likert scale. The questionnaire begins with five demographic questions, followed by 27 items (PR: items 1-3, PROB: items 4-6, IQ: items 7-10, HM: items 11-13, SP: items 14-16, PS: items 17-21 and CS&L items 22-27) corresponding to five factors (PR, PROB, IQ, HM, and SP) adopted from Prasetyo et al.'s (2021) scale during the pandemic (January 2021 to February 2022) and corresponding to four factors (PR, IQ, HM, and PS) after the pandemic (January 2023 to January 2024), as indicated in Appendix A.

Before collecting the study data, the questionnaire was pre-tested with a small group of participants to ensure the clarity and reliability of the measurement methodology. Adjustments were made based on feedback to improve the questionnaire's comprehensibility and format; social media and e-mail campaigns were used to reach respondents through online platforms to reach a wide range of consumers using AI-enabled food delivery services. The survey was conducted using Google Forms, which provided an easy and efficient data collection process. The survey gathered data on demographics and answers about customer satisfaction, loyalty, and elements affecting AI-driven food delivery services. In the context of AI-driven food delivery systems during and after the pandemic, the study focused on variables identified in the literature as significant factors influencing CS&L. These variables include price reduction, promotion benefits, information quality, hedonic motivation, and safe packaging perceptions. When formulating the hypotheses for this study, the choice of variables was determined mainly by the characteristics and limitations of the available dataset. In particular, some variables that would generally be relevant were not included because they were not well represented in the collected data. This led to the exclusion of Perceived Severity (PS) (H6d) during the pandemic and Promotion Benefits (PROB) (H2a) and Safe Packaging (SP) (H5a) after the pandemic.

Multiple regression analysis assessed the relationships between the dependent factors (CS&L) and the independent variables (price reduction, promotion benefits, information quality, hedonic motivation, and safe packaging perceptions). The measurement tool (scale), CS&L, was developed by Prasetyo et al. (2021). This approach facilitated the simultaneous analysis of factors such as price discounts, promotional effects, information quality, hedonic motives, and perception of safe packaging regarding satisfaction and loyalty. It facilitates a comprehensive analysis of these factors' impact on satisfaction and loyalty. This analysis helped understand the impact of each independent variable on CS&L. Data were analysed using SPSS, and multiple regression analysis was performed to evaluate the relationships between variables.

Results

The demographics of the participants who took place in the survey during and after COVID-19 were presented in Table 1. Most respondents during the pandemic were female (71.9%), and this trend continued post-pandemic (83.9%). Age distribution indicates a significant presence of younger participants, with those aged 18-24 accounting for 43.1% during and 85.9% after the pandemic. The services used during the pandemic show a heavy reliance on 'Yemeksepeti', a food delivery service, which remained high post-pandemic.

Table 1: Participants' Demographics in the Survey

		During COVID-19 Total(N=153) Ratio	Post-COVID-19 Total (N=141) Ratio
(1) Gender (%)	Female	110 (71.9)	83 (58.9)
	Male	43 (28.1)	58 (41.1)
(2) Age (%)	18-24	66 (43.1)	121 (85.9)
	25-34	28 (18.3)	15 (10.6)
	35-44	23 (15.0)	3 (2.1)
	45-54	19 (12.4)	2 (1.4)
	55 and above	17 (11.2)	0 (0.0)
(3) The AI-driven Food Delivery Service (%)	Acikinca	2 (1.3)	1 (0.7)
	Getir Yemek	34 (22.2)	20 (14.2)
	Tıkla Gelsin	1 (0.7)	1 (0.7)
	Trendyol Yemek	15 (9.8)	53 (37.6)
	Yemeksepeti	100 (65.3)	65 (46.1)
	Yemeksiparisi	1 (0.7)	1 (0.7)
(4) The AI-Driven Food Delivery Service frequency used	1-3	79 (51.6)	63 (44.7)
	4-6	37 (24.2)	41 (29.1)
	7-9	12 (7.8)	18 (12.8)
	10 and above	25 (16.4)	19 (13.4)
(5) Family member	1	12 (7.8)	6 (4.3)
	2	29 (19.0)	7 (5.0)
	3	48 (31.4)	38 (27.0)
	4	42 (27.5)	58 (41.1)
	5	15 (9.8)	22 (15.6)
	6	5 (3.2)	6 (4.3)
	7 and above	2 (1.3)	4 (2.7)

Source: Produced by the author.

The descriptive statistics for each construct during and after the pandemic are in Table 2 and Table 3. The skewness and the kurtosis values, for which the threshold values were between -1 and 1 according to Hair, Black, Babin, and Anderson, R. E. (2013), were satisfied, supporting the normality assumption. Standardised residuals were used to check for outliers or extreme values, explicitly identifying any residuals greater than ±3 standard deviations (SD). It was observed that no extreme values were present, as all residuals ranged between -1 and +1, except the variables listed in Table 2 and Table 3. These variables do not satisfy the criteria for normal distribution, as their skewness and kurtosis values surpass acceptable limits. For instance, during COVID-19, PS exhibited a skewness of 2.46 and a kurtosis of 7.51, while PROB showed a skewness of 2.69 and a kurtosis of 8.33. Additionally, for the post-COVID-19 period, SP had a skewness of 2.42 and a kurtosis of 7.18.

Table 2: Mean (M), Standard Deviation (SD), Skewness (SK), and Kurtosis (RKU) Values for Each Construct (Model 1) in the During COVID-19 Pandemic

DURING COVID-19 (Model 1)						
Constructs	**N**	**Items**	**M**	**SD**	**SK**	**RKU**
PR	153	3	3.27	0.87	-0.11	-0.59
PROB	153	3	3.97	0.87	-0.85	0.13
IQ	153	4	3.96	0.89	-0.72	0.36
HM	153	3	3.74	0.88	-0.36	-0.37
SP	153	3	3.96	0.79	-0.84	0.96
PS	153	5	2.22	2.77	2.46	7.51
CS&L	153	6	3.84	0.82	-0.46	0.03

Source: Produced by the author.

Table 3: Mean (M), Standard Deviation (SD), Skewness (SK), and Kurtosis (RKU) Values for Each Construct (Model 2) in the Post-COVID-19 Pandemic

POST COVID-19 (Model 2)						
Constructs	**N**	**Items**	**M**	**SD**	**SK**	**RKU**
PR	141	3	2.75	0.87	0.14	-0.43
PROB	141	3	2.70	3.13	2.69	8.33
IQ	141	4	3.94	0.84	-0.59	0.03
HM	141	3	3.67	0.91	-0.22	-0.86
SP	141	3	3.85	3.67	2.42	7.18
PS	141	5	3.45	0.88	-0.33	-0.36
CS&L	141	6	3.67	0.75	-0.04	-0.55

Source: Produced by the author.

Seven constructs (PR, PROB, IQ, HM, SP, PS, CS&L) were used to build the during and post-COVID-19 model. Table 4 and Table 5 show a model of strong internal consistency as evidenced by Cronbach's alpha (CA), composite reliability (CR) and the average variance extracted (AVE) values for both the COVID-19 pandemic and post-pandemic periods. According to Hair, Sarstedt, Ringle, and Gudergan (2017), all AVE values should exceed 0.5, and all constructs for both models were used to represent these periods to confirm validity. They suggest that CR values should exceed a threshold of 0.7, and this criterion is met for all CR values, indicating a good fit. Furthermore, Hair, Black, Babin, and Anderson (2010) suggest that all factor loadings should exceed 0.7, and all values meet this criterion in Tables 4 and 5.

In the During-COVID19 model, Table 4 shows that PR has three components with factor loadings ranging from 0.691 to 0.731, CA 0.904, CR 0.751 and AVE 0.501; PROB has three components with factor loadings ranging from 0.693 to 0.753, CA 0.843, CR 0.763 and AVE 0.519; IQ consists of four items with factor loadings ranging from 0.715 to 0.801, CA 0.893, CR 0.841 and AVE 0.570; HM has three items with factor loadings ranging from 0.646 to 0.794, CA 0.848, CR 0.756 and AVE 0. 510 items; SP three items with factor loadings ranging from 0.660 to 0.769, CA 0.896, CR 0.751 and AVE 0.502; CS&L six components with factor loadings ranging from 0.652 to 0.785, CA 0.870, CR 0.876 and AVE 0.541.

Table 4: Indicators, Cronbach's Alpha (CA), Composite reliability (CR), Average variances extracted (AVE) and Standardised Loadings (SL) for Model 1 during COVID-19

During COVID-19 (Model 1)	Indicators	Cronbach's Alpha	CR	AVE	SL
PR (Items 1-3)	**PR1**				0.731
	PR2	0.904	0.751	0.501	0.701
	PR3				0.691
PROB (Items 4-6)	**PROB1**				0.753
	PROB2	0.843	0.763	0.519	0.693
	PROB3				0.713
IQ (Items 7-10)	**IQ1**				0.739
	IQ2	0.893	0.841	0.570	0.801
	IQ3				0.763
	IQ4				0.715
HM (Items 11-13)	**HM1**				0.694
	HM2	0.848	0.756	0.510	0.794
	HM3				0.646
SP (Items 14-16)	**SP1**				0.693
	SP2	0.896	0.751	0.502	0.660
	SP3				0.769
CS&L (Items 22-27)	**CSL1**				0.774
	CSL2	0.870	0.876	0.541	0.759
	CSL3				0.691
	CSL4				0.742
	CSL5				0.785
	CSL6				0.652

Source: Produced by the author.

Table 5 shows that in the post-COVID19 model, PR had three components with factor loadings ranging from 0.620 to 0.780, CA 0.867, CR 0.753 and AVE 0.506; IQ had four items with factor loadings ranging from 0.698 to 0.790, CA 0.846, CR 0.846 and AVE 0.579; HM consists of three items with factor loadings ranging from 0.632 to 0.797, CA 0.835, CR 0.785 and AVE 0.552. PS consists of five items with factor loadings ranging from 0.673 to 0.772, CA 0.825, CR 0.841 and AVE 0.515; CS&L consists of six items with factor loadings ranging from 0.739 to 0.793, CA 0.790, CR 0.885 and AVE 0.505.

Table 5: Indicators, Cronbach's Alpha (CA), Composite reliability (CR), Average variances extracted (AVE) and Standardised Loadings (SL) for Model 2 in the Post-COVID-19

Post- COVID-19 (Model 2)	Indicators	Cronbach's Alpha	CR	AVE	SL
	PR1				0.620
PR (Items 1-3)	PR2	0.867	0.753	0.506	0.725
	PR3				0.780
	IQ1				0.790
IQ (Items 7-10)	IQ2	0.846	0.846	0.579	0.698
	IQ3				0.772
	IQ4				0.779
	HM1				0,632
HM (Items 11-13)	HM2	0.835	0.785	0.552	0,788
	HM3				0,797
	PS1				0,748
	PS2				0,772
PS (Items 17-21)	PS3	0.825	0.841	0.515	0,673
	PS4				0,693
	PS5				0,697
CS&L (Items 22-27)	CSL1				0,783
	CSL2	0.790	0.885	0.505	0,793
	CSL3				0,772
	CSL4				0,751
	CSL5				0,792
	CSL6				0,739

Source: Produced by the author.

The correlation matrices in Tables 6 and 7 reveal the interrelationships among constructs during and after the pandemic. During the pandemic, 'Information Quality' (IQ) strongly correlated with 'Promotion benefits' (PROB) at 0.654. In the post-pandemic, the highest correlation was between 'Information Quality' (IQ) and 'Perceived Severity' (PS), at 0.474, suggesting a shift in the constructs' interdependencies over time.

Table 6: Correlation Matrices of Constructs for Model 1 During COVID-19

Constructs	PR	PROB	IQ	HM	SP	CS&L
PR	1					
PROB	.331	1				
IQ	.398	.654	1			
HM	.427	.545	.489	1		
SP	.317	.508	.538	.485	1	
CS&L	.476	.677	.760	.654	.604	1

Source: Produced by the author.

Table 7: Correlation Matrices of Constructs for Model 2 in the Post-COVID-19

Constructs	PR	IQ	HM	PS	CS&L
PR	1				
IQ	.228	1			
HM	.178	.312	1		
PS	.180	.474	.239	1	
CS&L	.321	.544	.549	.269	1

Source: Produced by the author.

Research hypotheses for Model 1: During COVID-19

Model 1: Y (CS&L) = 0.060+ (0.082) * PR + (0.135) * PROB + (0.380) * IQ+ (0.233) * HM+ (0.151) * SP+e

For Model 1 (during COVID-19), the results of the Breusch-Pagan test show that the Lagrange multiplier statistic = 7.89, p-value = .080. These results confirm that the homoscedasticity assumption is also met for Model 1. The fact that the homoscedasticity assumption is met in both models indicates that the variance of the error term is constant at different levels of the independent variables, which guarantees the reliability of the statistical results.

Table 8: Multiple Regression Results of the Proposed Model 1

During COVID-19	Constructs	B	Standard error	Beta	T	P	F	Model (p)	Adj. R^2	Durbin Watson
Satisfaction & Loyalty	Constant	0.060	.205		.292	.771	77.242	0.000*	0.715	1.697
	Price Reduction	0.082	.038	.106	2.142	.034				
	Promotion Benefits	0.135	1.394	.164	2.650	.009				
	Information Quality	0.380	.057	.411	6.644	.000				
	Hedonic Motivation	0.233	.053	.248	4.408	.000				
	Safe Packaging	0.151	.057	.146	2.670	.008				

Source: Produced by the author.

In Table 8 for Model 1, the results of the regression model during the COVID-19 pandemic indicate that the two factors that positively affect CS&L the most are information quality ($\beta = 0.38$, $p<.001$) and hedonic motivation ($\beta = 0.23$, $p<.001$). CS&L is also positively impacted by price reduction ($\beta = 0.08$, $p = .03$) and safe packaging ($\beta = 0.15$, $p = .008$), although these effects are less pronounced than those of information quality and hedonic motivation. Additionally, promotion benefits have a significant positive effect ($\beta=0.13$, $p=.009$). With an adjusted R-square of .715, the independent variables account for 71.5% of the variation in CS&L. Given that the Durbin-Watson statistic is 1.697, there is little positive autocorrelation among the error terms (Durbin & Watson, 1950).

Research hypotheses for Model 2: Post-COVID-19

Model 2: Y (CS&L) = 0.621+ (0.091) * PR+ (0.309) * IQ+ (0.287) * HM+ (0.152) * PS+e

The Breusch-Pagan test was applied to both models to test the assumption of homoscedasticity (constant variance). For Model 2 (post-COVID-19), the results of the Breusch-Pagan test show a Lagrange multiplier statistic = 9.23, p-value = .065. The p-value is above the significance threshold of .05, so the model has no significant evidence of variance. This indicates that the assumption of equivariance is met for Model 2.

Table 9: Multiple Regression Results of the Proposed Model 2

Post-COVID-19	Constructs	B	Standard error	Beta	T	P	F	Model (p)	Adj. R^2	Durbin Watson
Satisfaction & Loyalty	Constant	0.621	.265		2.340	.021	34.517	0.000*	0.489	1.995
	Price Reduction	0.091	.045	.130	2.047	.043				
	Information Quality	0.309	.060	.344	5.197	.000				
	Hedonic Motivation	0.287	.055	.348	5.180	.000				
	Perceived Severity	0.152	.059	.179	2.585	.011				

Source: Produced by the author.

In Table 9 for Model 2, Information quality ($\beta=0.30$, $p<.001$) and Hedonic motivation ($\beta=0.28$, $p<.001$) remain the most significant factors influencing CS&L in the post-pandemic period. CS&L is significantly affected by perceived severity ($\beta = 0.15$, $p = .01$). Information quality ($\beta=0.30$, $p<0.001$) is still significant even though it has somewhat declined from the period before. The price reduction effect ($\beta=0.09$, $p=.04$) has lessened. The model's adjusted R-square of .489 indicates that the constructs account for 48.9% of CS&L. There is no autocorrelation between the error terms, as indicated by the Durbin-Watson statistic 1.995 (Durbin & Watson, 1950).

Table 10 summarises the hypotheses accepted or not tested during and after the pandemic, clearly depicting the results obtained.

Table 10: Summary of Hypotheses Testing Results

Hypothesis	Description	Period	Status
H1d	Price reduction affects CS&L	During the pandemic	**Accepted**
H1a	Price reduction affects CS&L	After the pandemic	**Accepted**
H2d	Promotion benefits affect CS&L	During the pandemic	**Accepted**
H2a	Promotion benefits affect CS&L	After the pandemic	**It could not be tested**
H3d	Information quality affects CS&L	During the pandemic	**Accepted**
H3a	Information quality affects CS&L	After the pandemic	**Accepted**
H4d	Hedonic motivation affects CS&L	During the pandemic	**Accepted**
H4a	Hedonic motivation affects CS&L	After the pandemic	**Accepted**
H5d	Safe packaging affects CS&L	During the pandemic	**Accepted**
H5a	Safe packaging affects CS&L	After the pandemic	**It could not be tested**
H6d	Perceived severity affects CS&L	During the pandemic	**It could not be tested**
H6a	Perceived severity affects CS&L	After the pandemic	**Accepted**

Source: Produced by the author.

This summary compares the factors affecting customer satisfaction and loyalty during and after the pandemic, emphasising consumer priorities and behaviour changes over time.

Discussion and conclusion

In Türkiye, every construct in both models significantly affects CS&L. However, the ranking and strength of the most influential factors differ between the two periods. During the pandemic, the most potent effects are seen with information quality and hedonic motivation, while post-pandemic, the influence of hedonic motivation and information quality continues, but the impact of perceived severity also comes to the forefront. The emphasis on information and safety during the pandemic evolves to prioritise hedonic experiences and managing perceived risks afterwards. In conclusion, these findings suggest that businesses and service providers should consider hedonic motivations and perceived severity more in shaping customer experiences post-pandemic. While the impact of factors like price reduction and promotion benefits may have diminished, they continue to be significant elements. Understanding these changing customer dynamics can provide competitive advantages for businesses and strengthen customer loyalty.

During the pandemic, promotion benefits (PROB) and safe packaging (SP) were essential variables in guaranteeing customer fulfilment and loyalty. In any case, post-pandemic, the importance of these variables diminished. This will be credited to the changing hazard perceptions of consumers. Amid the widespread, there was a high level of concern concerning the transmission of the virus through surfaces, which made safe packaging a crucial element. As this chance diminished within the post-pandemic period, buyers did not prioritise packaging safety to the same degree. So also, advancement benefits played a key part during the pandemic as money-related instability expanded cost affectability among customers. Post-pandemic, as financial stability progressed, the need for promotions decreased, with customers focusing more on the quality and involvement of the benefit instead of cost decreases or uncommon offers. This move highlights how buyer needs advanced from quick concerns of security and cost-saving to a more experience-driven approach.

Perceived severity (PS) emerged as an important factor for the first time following the pandemic. While previous research has emphasised the importance of perceived seriousness during the pandemic, findings show that consumers continue prioritising health-related issues, particularly long-term risks, in the post-pandemic context. Even though the immediate risks of the pandemic have decreased, this continued focus could be attributed to increased awareness of potential future health emergencies and a broader shift toward health-conscious behaviour. The increased emphasis on health and safety after the pandemic has set new consumer expectations, with safety and risk management considerations integrated into decision-making processes. Companies that recognise and address these ongoing concerns can consistently prioritise transparency to increase customer trust and loyalty.

Following the pandemic in Türkiye, young (Generation Z) consumers' engagement with digital and delivery services increased, indicating a notable shift towards online platforms. The reliance of this group of people emphasises how important AI-driven services are in adjusting to shifting customer preferences. The stability of consumer valuations of price reduction, information quality, and hedonic motivation despite the pandemic's disruptions highlights the significance of these elements in CS&L.

AI-driven projects have successfully addressed these needs by highlighting the importance of personalisation and high-quality information. Examples of these projects include working with chefs to create virtual culinary experiences and improving menu transparency.

The importance of positive and educational online experiences is highlighted by the persistence of hedonic motivation and information quality as important predictors of CS&L both during and post-COVID-19, as illustrated in Model 1 and Model 2.

Prasetyo et al. (2021) and Pal, Funilkul, Eamsinvattana and Siyal (2022) mentioned the significance of hedonic motivation and information quality. For instance, Yemeksepeti and other AI-driven services should collaborate with renowned chefs to produce virtual cooking classes and food-tasting events for hedonic motivation. To promote openness and trust, they should also create a "Know Your Chef" section with detailed chef biographies and hygiene certificates.

Personalisation and user experience should be prioritised in AI-driven systems to enhance the quality of the information. Additionally, it is crucial to guarantee that information regarding products and services is accurate, comprehensible, and all-inclusive. Features contributing to customer satisfaction include detailed product descriptions, excellent photos, and reliable reviews. For example, each menu item listed on Yemeksepeti or other AI-driven services could have a detailed description beyond the necessary ingredients. This description can include details about the dish's origins, method of preparation, potential unusual flavours, and suggestions for serving, such as sides or drinks. For instance, a pizza listing may specify the type of wood used in the oven, the source of the mozzarella cheese, and the method by which the chef infuses their unique flair into the sauce. Yemeksepeti and other AI-powered services may also organise virtual food festivals, where patrons can peruse and order from a carefully selected selection of restaurants offering menu items that are only available for a short period. Real-time cooking demonstrations and online kitchen tours are examples of how to add entertainment to this.

Longgang and Ming (2023) covered its importance in discussing perceived severity. It has been considered a crucial element, suggesting a shift in customer priorities reflecting health and safety worries even after the pandemic. With Yemeksepeti or other AI-powered services, users can create meal plans based on their dietary requirements, giving the app a fun and interesting feature. "Build Your Week: A Personalised Meal Planner," which can suggest meals from different restaurants based on the user's preferences and dietary needs, can help make meal ordering more than a chore. Additionally, it uses chatbots driven by AI to provide personalised meal recommendations based on the user's dietary needs, preferences, and mood. "Looking for something spicy or comfort food tonight?" a chatbot might inquire and then make menu item recommendations based on the user's choices. Detailed menu descriptions with ingredient lists, calorie counts, and dietary designations (vegan, gluten-free, keto-friendly, etc.) can also be included. This provides customers clarity and satisfies their dietary needs and preferences, assisting them in making decisions.

Carandang and Apritado (2022) addressed the importance of price reduction, promotion benefits (PROB), and safe packaging (SP). Though not as much, price reduction (PR) and safe packaging (SP) positively impact client loyalty and satisfaction. In terms of pricing and promotion, this highlights the importance of alluring promotions, secure delivery options, and aggressive pricing tactics during erratic times. Yemeksepeti and other AI-driven services can offer "Happy Hour" discounts during off-peak hours to increase orders during slow business periods. Offering a 10–15% discount on particular restaurants or menu items is one way to entice customers to place their orders between 2 and 5 PM in order to balance demand throughout the day. They would also allow customers to select environmentally friendly packaging when placing orders. This not only takes care of safety concerns but also upholds environmental sustainability. As a differentiator, these services could collaborate with restaurants that use recyclable or biodegradable packaging materials, emphasising their commitment to environmental sustainability.

The Machine Learning Model in Food Delivery, Recommendation Engine, NLP Implementation, Predictive Analysis, and Sentiment Analysis are the AI systems that are advised to develop food delivery systems. AI-driven food delivery systems can improve delivery efficiency or perform a variety of tasks, including classification, in a variety of applications by using machine learning algorithms like Decision Trees to predict delivery times and optimise routes (Lohit, Mujahid & Sai, 2022; Liu, Zhou, Höschle & Yu, 2023). They can improve ordering by tailoring meal recommendations according to past orders and user preferences (Vinagre, Jorge & Gama, 2018; Lohit et al., 2022). To make user interactions more manageable, they can also use natural language processing (NLP) in their chatbot to ask questions about orders and provide recommendations. Additionally, they can forecast demand in different locations using predictive analytics tools like neural networks and support vector machines (SVM) for clustering, which can help restaurants adjust their staffing and inventory levels (Kasza et al., 2022; Santi, Garrone, Iannantuoni & Del Curto, 2022). Additionally, they can use sentiment analysis tools like Python's TextBlob and Natural Language Toolkit (NLTK) to examine customer reviews and feedback to spot customer satisfaction patterns and areas that need improvement.

The research supports the Theory of Planned Behaviour (TPB) theoretical framework and provides insights about elements determining customer satisfaction and loyalty (CS&L) in AI-driven food delivery systems post-pandemic and during–the pandemic. Price reduction, promotional benefits, information quality, and hedonic motivation also pertain to the TPB attitude and behavioural intention component, determining the consumer's favourable or unfavourable evaluation of these services. This study contributes to the body of literature by presenting that cases of packaging and perceived severity are identified as influencers in the behavioural control element in times of environmental crisis— like COVID-19. The study found that confidence in safe packaging was an important factor in control and decision-making during the pandemic, but post-pandemic severity of perceived becomes more significant, suggesting consumer priorities are changing this year. The results are consistent with the tenets of the TPB that the factors affecting intention and behaviour change depend on situational variables, such as environmental context and perceived risk.

Managerially, the study indicates that while it will become wanting to focus on the irrelevant pandemic-related concerns of promotion benefits and safe packaging. Instead, businesses should enhance hedonic experiences and information quality to fulfil customer needs and maintain loyalty. This way, the service translates thrice as beneficial per use — cleverly playing with a customer's emotions and fulfilling their functional need. Finally, AI for food delivery systems should focus on health issues' perceived severity and longevity beyond the COVID-19 era.

Although this study offers some interesting insights, there are potential limitations. The sample might be skewed from a younger demographic and, therefore, not necessarily representative of the entire population. The survey's timing could also hinder how up-to-date a snapshot of an evolving market or the behaviours of customers it can offer. Further research could compare satisfaction and loyalty on platforms like Yemeksepeti and Getir with the help of ANOVA to scrutinise whether consumer preferences vary depending upon the service platform. Future research into demographic details such as marital status and family size could provide a comprehensive analysis. In addition, tests with adaptive and mediating variables such as income and technology compatibility could provide deeper insights into the determinants of platform preferences, such as the intention to continue using virtual shopping in the future.

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Appendix

Appendix 1: Questionnaire for During and After COVID-19

What is your gender?

a) Male

b) Female

c) Prefer not to say

d) Other (please specify)

Which age group do you belong to?

a) 18-24

b) 25-34

c) 35-44

d) 45-54

e) 55 and above

Which AI-driven food delivery service do you use most frequently?

a) Yemeksepeti

b) Getir Yemek

c) Trendyol Yemek

d) Tıkla Gelsin

e) Other (please specify)

How often do you use AI-driven food delivery services?

a) 1-3 times a month

b) 4-6 times a month

c) 7-9 times a month

d) 10 and above

How many family members are there in your household?

a) 1

b) 2

c) 3

d) 4

e) 5 or more

PR (Price Reduction)

- PR1: I consider food delivery e-commerce as offering fair prices.
- PR2: Although the restaurant and its menu are very compelling, the influence of the app can be seen in my ordering decisions.
- PR3: It motivates me to use their app because of price reduction schemes, in form of vouchers or coupons.

PROB (Promotion Benefits)

- PROB1: For the food delivery e-commerce app, I think the Navigation Bar helps.
- PROB2: The food delivery e-commerce app allows me to jump onto other pages and back to where I was.
- PROB3: I believe that dynamic filter helps me to find the restaurant or dish that I am talking about.

IQ (Information Quality)

- IQ1: Something new that I have found is food delivery e-commerce, which gives me the current offers on restaurants and food.
- IQ2: As far as food delivery e-commerce. I love to use it, because it is a believable information.
- IQ3: I feel that the food delivery e-commerce app sharing its data with me is at exactly the right level of granularity.
- IQ4: I think the information in the food delivery E-commerce app is structured well.

HM (Hedonic Motivation)

- HM1: I don't just use food delivery e-commerce for solve my basic problem.
- HM2: I spend more if we are talking about food delivery e-commerce because of the minimal purchase and promo.
- HM3: Using some food delivery e-commerce is such wonderful feeling when you donate a food/beverage to anyone.

SP (Safety Packaging)

- SP1: The packaging of the food I receive is clean and safe.
- SP2: I feel more comfortable ordering food if the packaging ensures hygiene.
- SP3: The use of safety seals on packages increases my trust in the delivery service.

PS (Perceived Severity)

- PS1: I understand social distancing regulations, so I use food delivery e-commerce instead of eating or buying my own food.
- PS2: I am hesitant to eat in restaurants, either due to COVID-19 or general health concerns.
- PS3: Food delivery services have helped meet my food needs both during and after the pandemic.
- PS4: I think food delivery e-commerce is a solution for the limited number of seats in restaurants due to social distancing restrictions.
- P5: Food delivery e-commerce helps me eat meals that I cannot cook when I am too lazy to eat out.

CS&L (Satisfaction and Loyalty)

- CSL1: I am satisfied with food delivery e-commerce's method of operation.
- CSL2: Overall, I am satisfied with food delivery e-commerce's service.
- CSL3: I always sign up for food delivery e-commerce promotions.
- CSL4: I would like to use food delivery e-commerce in the future.
- CSL5: I would recommend food delivery e-commerce to others.
- CSL6: I will share my experiences of using food delivery e-commerce with the public.