Understanding Continuance Intention of Merchants as End User in Online Food Delivery After COVID-19

Rahmat Yasirandi [1, 2], Bundit Thanasopon [1*]

[1] School of Information Technology, King Mongkut's Institute of Technology Ladkrabang, Bangkok, Thailand.

[2] Center of Excellence - Technological Society (CAATIS), Telkom University, Bandung, Indonesia.

Abstract

This study explores the continuance intention of merchants in using Online Food Delivery (OFD) services post-pandemic, employing an extended Expectation-Confirmation Model (ECM). While existing research on OFD predominantly examines food consumers, this study focuses on the merchant side and investigates how confirmation, perceived usefulness, satisfaction, perceived risk, and perceived critical mass influence their continuance intention. Using Structural Equation Modeling (SEM) on data collected from 378 Indonesian merchants, the findings highlight several critical factors. Perceived critical mass fosters platform adoption by creating a sense of widespread utility, while perceived risk indirectly affects continuance intention through its impact on satisfaction, emphasizing the need to address merchants' concerns. This research enhances the understanding of merchant behavior in the OFD ecosystem by incorporating context-specific factors that influence their decisions. The findings offer practical recommendations for OFD providers to improve system reliability, mitigate perceived risks, and foster a robust user community to ensure sustained engagement. Future studies could build on these insights by investigating similar dynamics in different regions or by including other stakeholders, such as delivery drivers, to provide a broader understanding of the OFD ecosystem.

Keywords: Online Food Delivery; Merchants; Expectation-Confirmation Model (ECM); Continuance Intention.

1. Introduction

This study builds on previous research examining the evolution of food delivery services in Indonesia, which highlighted significant changes beginning in the early 2010s with the emergence of two dominant models: restaurant-based delivery and e-commerce platforms, collectively referred to as Online Food Delivery (OFD) platforms [1]. OFD services have undergone a significant transformation, reshaping the food and hospitality industry globally. Over time, the OFD model became the leading approach, driving innovation and consumer adoption. However, the COVID-19 pandemic marked a pivotal moment in OFD's evolution, fundamentally changing consumer behavior and business operations in the food industry [2]. The rapid expansion of OFD platforms post-COVID-19 is attributed to shifts in consumer behavior and the platforms' adaptability to evolving demands. For consumers, OFD services offered safety and accessibility during COVID-19 restrictions, while for merchants, they provided a critical channel to maintain business continuity. Studies further reveal that convenience and trust have become critical factors influencing consumer

loyalty and OFD adoption during the endemic phase [3]. Despite the reopening of dine-in options globally, OFD platforms remain a preferred choice due to their convenience and ability to meet evolving consumer expectations. A study from South Korea shows that consumers continue to prefer OFD services due to their convenience, reliability, and ease of use, even after dine-in options reopened [4]. Research highlights the lasting impact of high service quality during the pandemic, with over 70% of consumers in Malaysia and Australia expressing satisfaction and a desire to continue using OFD platforms post-pandemic [5, 6]. In Malaysia, consumer attitudes toward OFD services during and after the pandemic have been explored, revealing that convenience and reliability remain critical factors driving consumer loyalty [5]. Similarly, research from India highlights that service quality outweighs cost concerns, with 65% of respondents willing to pay service fees for the convenience of OFD [7]. In Indonesia, 28.5% of consumers actively promote OFD services through word-of-mouth, reflecting high satisfaction levels [8]. These findings underscore the lasting impact of the pandemic on consumer habits.

Recent studies have broadened the understanding of OFD dynamics, emphasizing their impact on both consumers and merchants. For instance, research on market thickness has shown how optimizing OFD platform logistics—such as through efficient processing times and driver-order matching—improves delivery efficiency [9]. These advancements not only enhance consumer satisfaction but also deepen merchants' reliance on OFD platforms as essential tools for sustaining their operations. Building on the researchers' previous findings regarding the evolution of OFD services in Indonesia, this study emphasizes the critical role of merchants as end users in the OFD ecosystem [1]. Unlike consumers, merchants face distinct challenges, including operational dependencies, platform fees, and profitability pressures. Additionally, merchants hold a dual role: they are both users of the platforms and partners generating revenue for the OFD providers. This duality underscores the necessity of understanding merchants' perspectives to gain a comprehensive view of the ecosystem. However, most OFD research has focused predominantly on consumers, neglecting the behaviors, adaptations, and benefits experienced by merchants. This oversight creates a significant gap in understanding how merchants sustain and evolve their engagement with OFD platforms, particularly in the rapidly changing post-pandemic landscape. This study addresses these gaps by investigating the continued use of OFD services from the perspective of food merchants. Specifically, it aims to identify the key factors influencing merchants' continued adoption of OFD platforms in the post-pandemic era and develop an adoption model tailored to their operational and strategic needs. By shifting the focus from consumers to merchants, this research provides a more comprehensive understanding of the OFD ecosystem and offers practical insights for platform developers, policymakers, and the broader food industry.

The significance of this research is highlighted by the consistent growth in merchant adoption of OFD platforms in Indonesia. Data from Bank Indonesia indicates that the number of merchants using OFD platforms increased from 24.9 million in 2022 to 26.1 million in 2023 [10]. Leading platforms such as GoFood reported a 45% rise in new merchant partnerships in the same period [11, 12]. Gross Merchandise Value (GMV), a key indicator of OFD economic activity, also grew steadily, with Southeast Asia reporting an increase from 16.3 billion USD in 2022 to 17.1 billion USD in 2023, led by Indonesia [13]. These trends highlight the importance of understanding merchants' continuance use of OFD services to support their sustainability in an increasingly competitive environment. This research contributes to the existing literature by addressing a critical gap: the lack of focus on merchants as key stakeholders and end-users in the OFD ecosystem. While consumer behavior has been extensively studied, this research shifts the narrative to explore the challenges and opportunities faced by merchants.

The next section presents the theoretical model and explains the development of the proposed factors (Section 2). Section 3 details the research methods employed in this study. The results of the data analysis are presented in Section 4. The discussion related to the results from Section 4 is provided in Section 5. Finally, the conclusions, including recommendations and suggestions for future research, are presented in the final section, Section 6.

2. Theoretical Background and Hypothesis Development

2.1. Expectation-Confirmation Model (ECM)

The Expectation-Confirmation Model (ECM) is widely used to evaluate the adopters' continuance intention in adopting information systems and technologies (IS/IT) innovation [14]. ECM posits that adopters continued use of an innovation is influenced by their post-usage satisfaction, which is determined by the confirmation of pre-use expectations and perceived usefulness of the innovation. In the context of this study, ECM is particularly relevant to understanding food merchants' reliance on OFD, as it allows for examining the factors influencing their continuance decisions. As shown in Figure 1, first proposed by Bhattacherjee in 2001, ECM explains that several interrelated factors form positive associations. Starting with confirmation, the factor that reflects a user's post-adoption evaluation of whether their initial expectations have been met, it directly impacts their belief in the usefulness of the product or service. When expectations are confirmed, users are more likely to perceive the system as beneficial [15, 16]. This association describes what happens between confirmation and perceived usefulness.
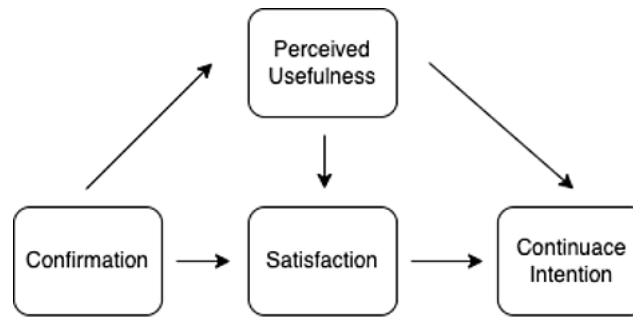
Figure 1. Expectation-Confirmation Model [14]

The ECM states that adopters' satisfaction is determined by two constructs: confirmation and perceived usefulness [17]. Confirmation has a positive effect on satisfaction in using IT because it shows the believed benefits. In contrast, disconfirmation (expectation levels are not met) can trigger failure to create satisfaction [18]. For instance, an online seller may feel dissatisfied if their expectations regarding delivery time, payment processing, or order accuracy are not met [19]. Meeting basic needs in an online marketplace is essential, and applications must ensure that these expectations are consistently met. Another critical construct related to satisfaction is perceived usefulness. This factor refers to the instrumental value that users derive from adopting an innovation. Perceived usefulness significantly influences the intention to continue using and adopting the technology, making it a primary driver in fostering continuance adoption [20]. According to ECM, this factor also directly influences post-adoption use of innovation (continuance intention). Some studies suggest that users tend to reuse technology after perceiving its usefulness [14]. In general, adopters feel inclined to reuse when they have benefited from the innovation consistently [21]. In addition to perceived usefulness, satisfaction also directly influences continuance intention. In this case, satisfaction with using the innovation can determine the user's attitude to repeatedly engage with the service. Essentially, if users' expectations are met or exceeded, and they find the system useful, they are likely to continue using it [22].

The versatility of the ECM has been demonstrated across various organizational contexts, particularly in evaluating continuance intention for different IS/IT innovations. Previous studies have extended ECM to areas like mobile services and online shopping, highlighting its effectiveness in predicting user behavior across diverse technologies. One of ECM's strengths lies in its adaptability, allowing researchers to extend the model with additional constructs that better capture unique aspects of specific contexts or technologies. This flexibility is evident in prior studies where researchers have enriched ECM by incorporating factors to reflect domain-specific characteristics. For example, perceived ease of use has been shown to mediate perceived usefulness in studies on e-motorcycles and mobile services, strengthening the explanatory power of ECM [23]. This adaptability makes it especially suitable for examining the continuance intention of food merchants in the post-pandemic environment, where unique dynamics like operational risks and network effects play a significant role.

Building on this foundation, ECM's adaptability is further supported by recent findings from other domains. For instance, studies have demonstrated that integrating additional variables into ECM enhances its capacity to explain continuance intentions, particularly in dynamic contexts, such as the adoption of mobile money beyond the lockdown period [24]. This present study leverages ECM's adaptability by incorporating two additional constructs, namely, perceived risk and perceived critical mass, reflecting the condition faced by food merchants in a post-pandemic environment. Such an approach not only addresses the contextual complexities of technological innovations, such as OFD, but also contributes to the growing body of research that contextualizes ECM to better understand adopter behavior.

2.2. The Proposed Model and Hypothesis

2.2.1. Influencing Factor of Perceived Usefulness

In the context of continuing to use an innovation, perceived usefulness is defined as the degree to which users believe that using a system will enhance their performance based on their initial and subsequent experiences [25]. In this study, perceived usefulness is specifically defined as restaurant owners' belief that adopting OFD services, from the pandemic to the post-pandemic era, enhances business operations. Perceived usefulness has been consistently demonstrated as one of the most influential factors in predicting user behavior after adoption [26]. For instance, merchants have reported increases in customer numbers after adopting the OFD service. This aligns with the Expectation-Confirmation Model (ECM), which posits that when merchants' initial expectations about the service's usefulness are confirmed, their satisfaction increases, leading to continued use of the service [14]. Specific benefits observed include increased sales transactions, easier customer acquisition through online orders, and overall revenue growth compared to traditional offline channels. These outcomes collectively demonstrate the perceived usefulness of OFD services in significantly improving business performance and operational efficiency.

Confirmation is defined as the merchant's perception of the suitability of the OFD application's expectations before adoption with actual performance after adoption [14]. It encompasses various aspects of the OFD service, such as the execution of delivery processes, the adequacy of information and tools provided for online transactions. Confirmation also involves evaluating whether the competitive advantages of partnering with the OFD service meet the restaurant's expectations and ensuring that the transaction experience does not fall short of these expectations. This factor, the confirmation, explains that the user's expectations may change time after time, depending on how much the expectation appears in the past before acceptance. Therefore, the process of confirmation directly impacts their perceived usefulness [27]. Previous studies indicate that confirmation is positively related to perceived value; when expectations are met or exceeded, users perceive greater value in the service [28]. For instance, when OFD services meet merchants' expectations by providing necessary tools and information, perceived usefulness increases. Conversely, a disappointing experience negatively impacts perceived usefulness. This factor suggests that users' expectations may change over time, depending on their experiences before acceptance. The confirmation that OFD services meet or exceed expectations thus leads to a higher perception of their usefulness, highlighting their benefits in enhancing merchant's business operations and competitiveness in the market. Thus, the relationship to perceived usefulness becomes positive. The ECM also explains that the higher the confirmation received, the more benefits the adopter will experience. Overall, confirmation strengthens perceptions of usefulness by ensuring expectations are consistently met. Therefore, the following hypothesis is proposed:

Hypothesis 1 (H1): Confirmation has a positive impact on Perceived Usefulness.

2.2.2. Influencing Factors of Satisfaction

In the ECM, satisfaction is a critical factor influencing adopters' continuance behavior [29]. For food merchants, satisfaction reflects their overall experience and success with OFD services. It includes evaluating whether the decision to adopt OFD services was wise, and whether the service met or exceeded expectations. This satisfaction includes various elements such as the decision to offer OFD services, the perceived wisdom of maintaining these services, and the overall experience with the OFD service [14]. Therefore, all these elements are included as indicators in the questionnaire to represent this factor (see Appendix). Positive satisfaction can be expressed through the restaurant's contentment with the decision to offer OFD services. Conversely, negative satisfaction is reflected in regret over the decision to adopt OFD services and an overall unsatisfactory experience with the service. Satisfaction is influenced by how adopters confirm that their expectations align with actual experiences [30]. The subjectivity of adopters in confirming their beliefs significantly impacts their satisfaction. Food merchants' confirmation of the conditions while using the OFD application has the potential to determine their satisfaction of the application's performance. Therefore, the following hypothesis is proposed:

Hypothesis 2 (H2): Confirmation has a positive impact on Satisfaction.

According to research before, not only with confirmation of expectations but also perceived usefulness significantly influences users' satisfaction [14]. As explained in the previous subchapter, perceived usefulness, through its indicators, measures the degree of usefulness believed by users since first adoption in the pandemic era. Like the confirmation factor, perceived usefulness also impacts the satisfaction factor. For instance, a study on information systems user behavior found that perceived usefulness significantly affects confirmation [31]. This means that when users perceive a system as highly useful, their initial expectations are more likely to be confirmed, which in turn enhances their satisfaction with the innovation. Similarly, another study investigating mobile internet users' continuance intention highlighted that perceived usefulness, along with cognitive absorption, positively influences confirmation and satisfaction [32]. Adopters who find the system beneficial are more likely to have their expectations met, leading to higher satisfaction. During the transition from the pandemic to the post-pandemic era, if several enhancements in order services are perceived as useful by the merchants, it will lead to positive confirmation. Therefore, this study proposes the Perceived Usefulness-Satisfaction association in the designed model. The following hypothesis is proposed:

Hypothesis 3 (H3): Perceived Usefulness has a positive impact on Satisfaction.

Perceived Risk is the degree to which the uncertainty and negative effects are obtained from engaging in the innovation adoption action [33]. In this study, perceived risk is defined as the uncertainty and potential negative outcomes experienced by restaurants in adopting OFD services. High perceived risk diminishes satisfaction and increases hesitation, reducing adopters' trust in the platform [34]. Therefore, perceived risk provides a crucial evaluation of the satisfaction obtained by adopters. Performance-based risk perceptions negatively impact users' adoption decisions as perceived risk increases users' hesitation and ultimately reduces their satisfaction with the technology. n the transition era from pandemic to post-pandemic, if the idea of using technology is accompanied by perceived risk, the satisfaction with adopting OFD services will decrease. For instance, during the transition from pandemic to post-pandemic, if perceived risks, such as transaction errors, increase, merchants' satisfaction with adopting OFD services is likely to decrease [35, 36]. The negative impact of perceived risk highlights its significant role in shaping satisfaction. Therefore, the following hypothesis is proposed:

Hypothesis 4 (H4): Perceived Risk has a negative impact on Satisfaction.

2.2.3. Influencing Factor of Perceived Critical Mass

Perceived Critical Mass refers to the idea that a platform's large user base compels others to join due to the opportunities they may otherwise miss out on [37]. When a platform reaches critical mass, it becomes self-sustaining because the large number of users attracts even more users. In this study, perceived critical mass is defined as a condition where a significant number of users (both merchants and consumers) drive merchants to join and adopt the OFD platform. If merchants find the platform efficient and beneficial, this increases the likelihood of achieving critical mass, thereby reinforcing the platform's attractiveness. This concept helps understand how OFD grow and become essential for users, especially merchants and their businesses. For example, previous studies have shown that if many customers use a specific online marketplace or social media platform, merchants feel compelled to join to reach these customers [38]. On the other hand, perceived usefulness, as previously explained, is the degree to which users believe that using a platform will benefit them. This positively impacts perceived critical mass. When users find a platform useful, they are more likely to use it extensively, thereby attracting more users and helping the platform reach critical mass [39]. Another study has shown that perceived usefulness can drive adoption rates and contribute to a platform's success by encouraging more users to join, thus enhancing its perceived critical mass [40]. In this study, when merchants see the tangible benefits and efficiencies provided by the OFD application, they are more inclined to join, increasing the platform's user base and making it more attractive to other potential users. Therefore, there is a significant association between perceived usefulness and perceived critical mass. If merchants find an OFD efficient and beneficial, it increases the likelihood of achieving critical mass. This growing customer base attracts more merchants who do not want to miss out on substantial market opportunities, thereby reinforcing the platform's critical mass. Therefore, the following hypothesis is proposed:

Hypothesis 5 (H5): Perceived Usefulness has a positive impact on Perceived Critical Mass.

2.3. Influencing Factor of Continuance

The meaning of "continuance" refers to a situation where the adopter identifies the continuous use of an action or purpose that has been implemented [41]. Continuance intention refers to an individual's intention to continue using a particular technology over the long term. In this study, continuance intention is specifically defined as the restaurant's intention to continue using Online Food Delivery (OFD) services. This refers to the restaurant's intention to maintain the use of OFD services as a primary channel for sales and customer engagement, driven by the ongoing popularity and anticipated growth of these services among customers. Several indicators are used to measure continuance intention in the context of OFD services, as represented in the study's questionnaire. These indicators include the ability to connect with customers and maintain sales, the growing popularity of the innovation, and the strategic importance of these innovation even post-adoption [42]. This involves the restaurant's commitment to maintaining OFD services as a primary channel for sales and customer engagement, a decision driven by the ongoing popularity and anticipated growth of these services among customers. In the proposed model of this study, continuance intention is driven by several factors, starting with satisfaction. As previously discussed, satisfaction is a key factor in this model as directly influence the continuance intention [14]. Positive satisfaction can impact the restaurant's decision to continue adopting OFD services [43]. For instance, studies indicate that when users are satisfied, they are more likely to continue using the technology due to the positive experiences and perceived benefits. Conversely, negative satisfaction is reflected in regret over the decision to adopt OFD services during the pandemic era, resulting from an overall unsatisfactory experience with the service. This negative satisfaction can lead to discontinuance intentions as users may feel the service does not meet their expectations or needs. Therefore, the following hypothesis is proposed:

Hypothesis 6 (H6): Satisfaction has positive impact on Continuance to Use OFD services.

Another factor in the proposed model directly associated with continuance intention is the Perceived Critical Mass. Previous research indicates that perceived critical mass significantly influences users' intentions to continue using a technology [44]. Perceived critical mass shapes users' perceptions of the innovation's characteristics, thereby directly influencing their use intentions. When users believe that an innovation has reached a critical mass, they are more likely to adopt and continue using it. This highlights the importance of achieving and demonstrating critical mass in innovation to ensure continued user engagement and adoption. In another study, it was found that when adopters perceive a high level of adoption among others, they are more likely to continue using these platforms to leverage the benefits of a large, active user base [45]. The perception of a large user base (critical mass) positively influences the intention to continue using the platform. Users are more inclined to stay on a platform if they see a substantial number of active users, which enhances the platform's value and encourages continued adoption. Consequently, perceived critical mass plays a crucial role in ensuring continuance intention in the use of OFD. Therefore, the following hypothesis is proposed:

Hypothesis 7 (H7): Perceived Critical Mass has positive impact on Continuance to Use OFD services.

For the last factor influencing continuance intention, perceived risk plays a critical role. As previously defined, perceived risk refers to the uncertainty and potential negative consequences that users associate with adopting a new technology or service [46]. Research has shown that perceived risk negatively impacts users' intentions to continue using

mobile services. The uncertainty and potential negative outcomes associated with these services increase users' hesitation and reduce their trust in the service [47]. In the FinTech sector, users' risk perception, primarily driven by concerns over financial and security risks, has been found to negatively influence their intention to continue using these services [48]. Users who perceive high levels of financial and security risks are more likely to discontinue using FinTech services, as these perceived risks outweigh the benefits. Similarly, in the context of OFD applications, perceived risk plays a significant role in shaping users' continuance intention. High perceived risk, such as concerns if OFD transaction errors were to occur, there is worry that merchants would be unable to get compensation, deters them from continuing to use OFD services. This high level of perceived risk can lead to a decrease in the ongoing willingness of users to continue with the OFD services. Therefore, the following hypothesis is proposed:

Hypothesis 8 (H8): Perceived Risk has negative impact on Continuance Intention to Use OFD Application.

This study leverages the adaptability of the ECM by incorporating two additional constructs: Perceived Critical Mass and Perceived Risk. These constructs were selected for their theoretical and practical relevance to the OFD ecosystem. Perceived Critical Mass emphasizes the influence of a growing user base on sustained use. As discussed in the subchapter "Perceived Critical Mass," this construct is defined as the perception of a platform's widespread use among customers and merchants, which creates a compulsion for further participation due to the perceived benefits of being part of a well-established network [37]. Similarly, Perceived Risk reflects concerns about financial, operational, and security-related uncertainties, as supported by research on technology adoption. The subchapter "Perceived Risk" elaborates on the role of perceived risk in shaping user satisfaction, highlighting how such uncertainties can adversely affect the willingness to continue using a platform [33]. The expanded model builds on the core ECM constructs—Confirmation, Satisfaction, Perceived Usefulness, and Continuance Intention—by hypothesizing six positive impacts that enhance the likelihood of continued OFD use, alongside two negative impacts related to perceived risk (see Figure 2). This integration of constructs contributes to the theoretical discourse on the proposed adoption model in several ways. First, it introduces new pathways (H4, H5, H7, and H8), demonstrating the impact of perceived critical mass and perceived risk in this study. Second, by shifting the focus from consumers to merchants, this study addresses a critical gap in the literature, providing a more nuanced understanding of the OFD services. Third, the simultaneous inclusion of perceived critical mass and perceived risk within the ECM enhances its explanatory power, enabling a comprehensive framework tailored to the specific context of Indonesian Food Merchant in facing post pandemic.
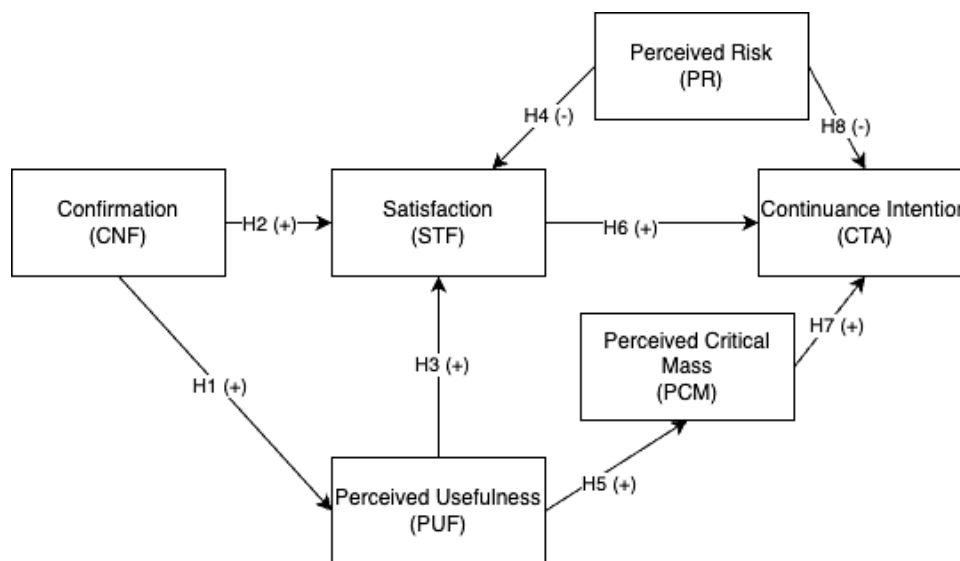

Figure 2. The proposed OFD application continuance intention model

3. Research Methodology

The methodology employed in this study is based on the Research Onion, a multi-layered representation of the research process Proposed by Saunders et al. (2007) [47], the Research Onion outlines the key decisions researchers make, starting from the outermost layer (research philosophy) to the innermost layers (data collection and analysis techniques) [49]. Each layer provides a conceptual guide for building a coherent and structured research methodology [50]. This layered approach ensures that the study aligns with its objectives and the research context, enabling systematic exploration of the phenomena under investigation. The outermost layer of the Research Onion, Research Philosophy, defines the fundamental assumptions that guide the research process. It establishes the study's theoretical foundation, influencing all subsequent decisions. This study adopts Positivism as its research philosophy. Positivism emphasizes objectivity, evidence-based propositions, and quantifiable measures [51]. Positivism aligns with the study's aim to test

hypotheses quantitatively using statistical analysis of questionnaire data collected from food merchants in Indonesia. By adopting positivism, this study seeks to empirically validate the proposed model of adoption and continuance intention for OFD services. The philosophy's emphasis on hypothesis testing and statistical rigor supports the examination of the study's proposed constructs. The second layer, Research Approach, defines the study's logical structure. This research employs a Deductive Approach, a top-down framework where hypotheses are derived from existing theories and tested empirically [52]. Deduction is particularly well-suited to studies grounded in positivism, as it emphasizes objectivity and the systematic validation of theoretical constructs through empirical observation. The Deductive Approach aligns with the study's objectives, enabling statistical testing of hypotheses while addressing determinant factors faced by food merchants adopting OFD services post-COVID-19. By leveraging this approach, the study systematically evaluates whether the proposed hypotheses align with observed data, providing robust evidence for the research problem. Aligned with the Deductive Approach, this study adopts a Quantitative Method, using structured data collection and analysis techniques to objectively evaluate the research hypotheses. This method is particularly suitable for studies requiring structured tools like questionnaires to collect numerical data that can be statistically analyzed [53].

The use of Quantitative Method ensures clarity of findings, providing robust evidence to address the research objectives. This study employs a Survey as its Research Strategy, a widely used method in quantitative research. Surveys are particularly suitable for examining food merchants in Indonesia, as they facilitate standardized data collection and precise hypothesis testing for constructs such as perceived risk and perceived critical mass. The study also adopts a Cross-Sectional Time Horizon, collecting data at a specific point in time. This design is ideal for capturing a snapshot of food merchants' reliance on OFD services during the post-pandemic period. Cross-Sectional studies are effective for understanding phenomena within a defined timeframe without the need for long-term data collection [54]. This approach allows the study to focus on immediate impacts, particularly those shaped by the period in facing post-pandemic environment. By outlining all layers of the Research Onion, this study establishes a coherent methodology that aligns with its objectives and research context. The Positivist Philosophy, Deductive Approach, Quantitative Method, Survey Strategy, and Cross-Sectional Time Horizon collectively form a robust framework for examining the determinants of food merchants' adoption of OFD services in the post-pandemic period. Figure 3 illustrates this workflow of the research design, which is divided into seven activities and three key phases: developing the research context, preparing to collect respondents, and analyzing and interpreting the data. This workflow ensures a systematic approach to achieving the study's objectives.
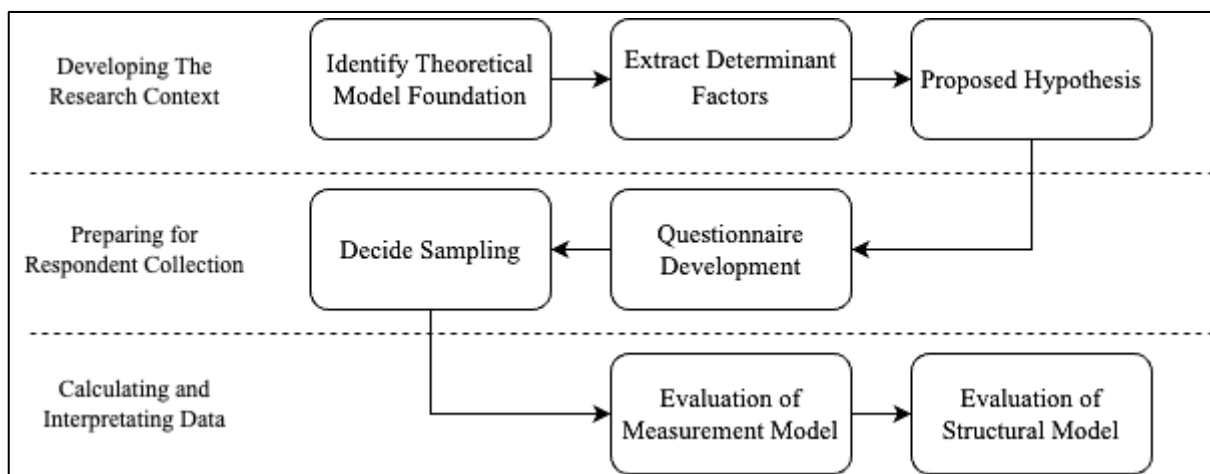

Figure 3. The workflow of this study

In the Developing Context phase, the research began by identifying the foundational theoretical model. This activity was completed in the earlier stages, during which the ECM was established as the primary framework for the study. Furthermore, determinant factors and proposed hypotheses were identified and developed, forming pathways that connect the various proposed factors. All these activities in the Developing the Research Context phase have been clearly presented and discussed in the previous chapter. The next phase, Preparing for Respondent Data Collection, focuses on two key activities: conducting a literature review to develop the questionnaire and determining the sampling strategy. For questionnaire development, measurement items were designed in the form of a structured questionnaire. A structured questionnaire is the most common tool for collecting quantitative data [55]. The questionnaire aligns with the previously defined methodological choice described earlier in this chapter. When the population has complicated explorations, a descriptive explanation in the form of a questionnaire can help explain the meaning of each factor in the proposed model. A comprehensive review of relevant literature was conducted to identify validated scales that could either be adapted or used as a basis for creating this measurement items. Additionally, the questions were adjusted to fit the organizational context of food merchants and the technological innovation of OFD to ensure relevance and applicability to the study's objectives. It was crucial to ensure that these items accurately represented the constructs while maintaining clarity,

specificity, and freedom from ambiguity. The outcome of the questionnaire development phase was a set of 26 items distributed across six constructs. These items are detailed in Table 1, which provides an overview of how each construct has been operationalized in this study.

Table 1. Measurement Items

Construct	Item	Measurements (*opposite)	References
Perceived Usefulness	PUF1	My restaurant has experienced an increase in number of customers after using OFD service.	[14]
	PUF2	After using OFD services, the sales transactions of my restaurant have increased.	
	PUF3	After using OFD services, gathering customers through online order has become easier.	
	PUF4*	I have found that the OFD service did increase revenue compared to offline channels.	
Confirmation	CNF1	The OFD's execution in my restaurant has met my expectations.	[14]
	CNF2	The OFD services gives me all the information and tools needed to place and execute online delivery transaction.	
	CNF3*	My online delivery transaction experience via OFD services falls short of my expectations.	
	CNF4	The competitive advantages of being a OFD's food merchant partner have met my expectations.	
	CNF5	I generally receive the level of services that I expect from OFD services.	
Satisfaction	STF1	I am satisfied with my restaurant's decision to offer OFD services.	[14]
	STF2	My restaurant choice to provide OFD services until now is a wise one.	
	STF3*	I am regretted with the earlier My restaurant's decision (during the pandemic) to adopt OFD services.	
	STF4*	My restaurant experience with using this OFD service was very unsatisfactory.	
Continuance Adoption	CTA1	My restaurant wants to continue providing OFD services rather than discontinue its use.	[14, 42]
	CTA2	The OFD service is still popular among my customers, and the trend is expected to continue rising.	
	CTA3	The OFD currently is and will be one of the restaurants commonly used selling channels, even after the pandemic.	
	CTA4*	If I could, my restaurant would like to discontinue use of OFD services.	
Perceived Risk	PR1*	I would feel secure sharing private information about my restaurant, such as transaction logs, revenue histories, and menu popularity trends, with OFD providers.	[56, 57]
	PR2	If OFD transaction errors were to occur, there is worry that restaurant would be unable to get compensation.	
	PR3	I worry about the potential occurrence of fraud and fake orders from OFD provider.	
	PR4	If something goes wrong with an OFD transaction, customers might give the restaurant a low rating and a complaint.	
	PR5	There is a risk that a transaction of transferring money or a standing order may not be processed.	
Perceived Critical Mass	PCM1	Many more people are still comfortable buying food through OFD services.	[37]
	PCM2	Among the customers who frequent my restaurant, a significant number of them chose OFD services.	
	PCM3	The people who have used OFD services to order are likely to continue using them in the future.	
	PCM4	Customers who have been using OFD since the pandemic are likely to continue using it.	

Following the development of measurement items, the next step was to determine the sampling strategy. Target respondents were Indonesian merchants who had been using Online Food Delivery (OFD) services since the early days of the COVID-19 pandemic in 2020. To ensure efficient and representative data collection, sample locations were systematically selected using the 2022–2023 ICT Development Index from the Indonesian Central Bureau of Statistics. The selected locations included major cities such as Jakarta, the capital city, with an ICT index score of 7.66, Yogyakarta with a score of 7.14, and Bali with a score of 6.49. Additional cities with the highest ICT index from each time zone in Indonesia were also included, such as Bandung in West Java Province (GMT +7), Samarinda in East Kalimantan Province (GMT +8), and Manado in North Sulawesi Province (GMT +9). This selection ensured that the sample represented diverse regions across the country while maintaining homogeneity within the sample by applying an ICT index threshold of >5.5 (medium to high ICT development). Despite collecting data from regions with varying time zones (GMT +7, +8, +9), the analysis considered the data as a unified population. This approach was justified by consistent digitalization parameters across regions, as the OFD platform operates with standardized features, ensuring a uniform experience for merchants nationwide. Additionally, government policies regarding digitalization in Indonesia are generally uniform. This approach aligned with the study's objective to derive insights from the overall population rather than focusing on subgroup comparisons. Cochran's Equation was used to calculate the required sample size, providing a systematic method that incorporates purposive sampling criteria. In this study, the variables were determined as follows are a 95% confidence level, a 5% margin of error, and an estimated valid proportion (p) of 0.5. Based on these parameters, the calculation yielded a minimum required sample size of 385 respondents.

To ensure robust analysis, data collection resulted in a total of 400 respondents, of which 378 were retained after the data cleaning process. Data collection occurred over four months (September to December 2023), involving at least 30 surveyors working simultaneously across the selected locations. This period marked a transitional phase toward post-pandemic recovery, during which the Indonesian government relaxed restrictions, allowing businesses to resume normal operations. Measuring merchants' intention to continue adopting OFD services during this time was particularly relevant, as it captured their behavior in a pivotal recovery period. A 5-point Likert scale was used in the questionnaire, enabling respondents to provide clear and consistent ratings. This standardization enhanced the reliability and validity of responses across constructs. The inclusion of cities with similar ICT infrastructure and the uniformity of OFD platform quality and national-level policies ensured consistency across the subset. As such, the collected data were analyzed as a single, unified sample group, without treating regional subsets as distinct for separate analysis. This approach ensures the robustness and clarity of the overall findings, focusing on the shared experiences of merchants using OFD services during the post-pandemic period. The final phase of this research focuses on analyzing and interpreting data to validate the proposed research model. This phase comprises two critical activities: the evaluation of the measurement model and the evaluation of the structural model, each addressing key aspects of the model's reliability, validity, and overall fit. This study employs Covariance-Based Structural Equation Modeling (CB-SEM) to analyze the data. CB-SEM is particularly suited for testing causal relationships in complex models with multiple interrelated constructs and indicators. Compared to Variance-Based Structural Equation Modelling (VB-SEM), CB-SEM is particularly advantageous due to its ability to assess overall model fit and handle highly interdependent variables, ensuring robust and reliable results [58]. The measurement model evaluation ensures that the constructs are accurately measured through their observed variables. The main steps include:

- Confirmatory Factor Loading: Verifies whether observed variables significantly load onto their latent constructs, with loadings greater than 0.7 indicating strong associations.

- Composite Reliability (CR): Assesses the reliability of each construct, with CR values exceeding 0.7 confirming consistent measurement.

- Convergent Validity: Ensures the indicators within a construct correlate well, evaluated through Average Variance Extracted (AVE), where AVE values greater than 0.5 are deemed adequate.

After validating the measurement model, the focus shifts to evaluating the structural model, which examines the relationships between constructs. The key steps include:

- Path Coefficients: Measure the strength and statistical significance ($p < 0.05$) of relationships between latent variables.

- Goodness-of-Fit Indices: Assess the overall model fit using metrics such as Chi-square/df, RMSEA (Root Mean Square Error of Approximation), CFI (Comparative Fit Index), and TLI (Tucker-Lewis Index). Acceptable values for these indices indicate that the structural model aligns well with the data.

- Squared Multiple Correlations (R^2): Evaluate the proportion of variance explained by the independent variables for endogenous constructs, with higher R^2 values indicating greater explanatory power.

If the evaluation identifies areas for improvement, model modifications may be undertaken. These could involve refining paths between constructs or introducing covariances between measurement errors to enhance the model's fit based on analytical insights. The results of these evaluations, including the detailed calculations and interpretations, will be comprehensively presented and discussed in the following chapter, offering valuable insights into the research findings and their implications.

4. Results and Discussion

4.1. Analysis of Measurement Model

In the first stage, the first calculate estimation results show that several loading factor values for the measurement items did not meet the cut-off value threshold, which should be above 0.7 to meet validity criteria [59]. The items with loading factors below this threshold are PUF4 (0.330), CNF3 (0.225), CNF4 (-0.005), CTA4 (0.348), PR2 (0.148), and PR5 (-0.138). These items are considered invalid due to their low loading factor values and their similarity to other questions with a similar meaning, which caused confusion for respondents and blurred understanding. For example, PUF4 overlaps with PUF1 and PUF2, which specifically address the increase in the number of customers and transactions. Therefore, PUF4 can be represented by PUF1 and PUF2, which are more specific in discussing the increase in customers and transactions. CNF3, which states that the online transaction experience did not meet expectations, is closely aligned in purpose with CNF1 and CNF5, which provide a clearer and more direct description of expectations. Therefore, CNF3 can be dropped without compromising the clarity of the model. CTA4, which expresses the desire to discontinue using OFD, conflicts with CTA1 and CTA2, which are more relevant and clearer in measuring the intention to continue using OFD. Finally, PR2 and PR5, which discuss transaction risks, are like PR3 and PR4, which are better at describing risks related to security and the impact of transaction errors.

Based on the results of the first calculation estimate, where certain items with low loading factors (such as PUF4, CNF3, CNF4, CTA4, PR2, and PR5) were removed, a second calculation was performed to refine the model. For more detailed results, Table 2 presents the findings from the second calculation, offering insights into the Loading Factors, Average Variance Extracted (AVE), and Composite Reliability (CR) for each construct and its associated indicators. These metrics are essential for assessing the validity and reliability of the model. In this second calculation, all remaining indicators display loading factors above the 0.7 threshold, indicating strong reliability for each indicator. This shows that each indicator contributes significantly to its respective construct. Additionally, AVE is critical for evaluating the convergent validity of the constructs. Like loading factors, AVE ensures that each construct captures more variance from its indicators than error variance. The AVE values for all constructs meet with the minimum threshold of 0.5, indicating that the constructs explain sufficient variance in their indicators [60]. Table 2 also shows the results from the second calculation estimate with strong Composite Reliability (CR) values across all constructs, indicating solid internal consistency and reliability. All constructs exceed the recommended threshold of 0.7, which is the standard for confirming that the indicators consistently measure the intended constructs with minimal error [60]. Perceived Usefulness (PUF), Confirmation (CNF), and Satisfaction (STF) have high CR values of 0.912, 0.946, and 0.962, respectively, indicating that their indicators reliably capture the constructs. While Continuance Intention (CTA) has a slightly lower CR of 0.817, it still demonstrates sufficient reliability. The strong loading factors, AVE, and CR values confirm the robustness of the measurement model. Overall, the results demonstrate that the model is reliable and valid, providing a solid foundation for further structural model analysis.

Table 2. The second calculate estimate of measurement model stage

Constructs	Indicators	Loading Factors	Average Variance Extraction (AVE)	Composite Reliability (CR)
PUF	PUF3	0.743	0.776	0.912
	PUF2	0.923		
	PUF1	0.900		
CNF	CNF1	0.898	0.885	0.946
	CNF2	0.792		
	CNF5	0.962		
STF	STF4	0.872	0.864	0.962
	STF3	0.873		
	STF2	0.892		
	STF1	0.899		
CTA	CTA1	0.707	0.599	0.817
	CTA2	0.758		
	CTA3	0.760		
PR	PR1	0.727	0.710	0.879
	PR3	0.774		
	PR4	0.846		
PCM	PCM1	0.814	0.686	0.897
	PCM2	0.780		
	PCM3	0.836		
	PMC4	0.751		

Note: PUF= Perceived Usefulness, CNF= Confirmation, STF= Satisfaction, CTA= Continuance Intention, PR= Perceived Risk, PCM= Perceived Critical Mass.

4.2. Analysis of Structural Model

To ensure that a model is considered ideal in a goodness of fit, it is generally required that at least four indices from various categories (such as Chi-Square, Probability, CMIN/DF, RMSEA, GFI, AGFI, TLI, and CFI) meet the "good fit" criteria [61]. This interpretation means the model aligns well with the collected sampling data. However, if an index closes to passing the good fit threshold, this may suggest that certain indicators have undue correlations with others [62]. For example, in this study, the GFI value approached the cut-off with a result of 0.896, while the accepted good fit criterion is ≥ 0.90. In such cases, one step that can be taken is to examine the modification indices (M.I.). This approach is supported by previous research, which suggests that using M.I. to identify and evaluate correlations between indicators can significantly improve the model fit [63]. Based on the M.I., STF4 was identified as having a high error correlation with STF3 (M.I.: 65.081) and STF2 (M.I.: 32.238). Therefore, STF4 need to be dropped to enhance the model fit, leading to the revised path diagram for the proposed model.

After removing STF4 and recalculate estimate of model fit, the model showed improvements in several goodness of fit indices, such as an increase in GFI to 0.914, as detailed in Table 3. This highlights the evaluating M.I. in optimizing the model within CB-SEM to achieve a better fit [63]. Although certain indices like Prob. and CMIN/DF still did not meet into the "good fit" category, Table 3 shows more than four other indices meet the "good fit" criteria. This result is sufficient to classify the proposed theoretical model as having an acceptable level of fit, as the collected data adequately explains the relationships between the constructs in the theoretical model.

Table 3. The second calculated estimate of model fit

Index	Cut of Value	Calculation	Category
Chi Square	≤ 341.395 (with d.f. 300 and prob 0.05)	335.277	Good Fit
Prob.	≥ 0.05	**0.000**	Unfit/ Not Fit
CMIN/DF	≤ 2.00	**2.338**	Unfit/Not Fit
RMSEA	≤ 0.08	0.060	Good Fit
GFI	≥ 0.90	0.914	Good Fit
AGFI	≥ 0.90	0.887	Marginal Fit
TLI	≥ 0.95	0.957	Good Fit
CFI	≥ 0.95	0.964	Good Fit

Table 4 presents the regression weights for the hypotheses. In line with standard statistical practice, a p-value of less than 0.05 indicates statistical significance [64]. Based on this threshold, 7 out of the 8 paths are significant, while 1 path, H8 (PR→CTA), is not significant with a p-value of 0.235, showing that perceived risk does not have a significant impact on continuance intention. Table 4 also provides the beta (β) values, which indicate the direction of the relationships. β values provide insights into the strength and direction of relationships, with values closer to 1 or -1 indicating stronger associations between variables [65]. A positive β value (closer to 1) reflects a positive relationship, meaning that as the independent variable increases, the dependent variable also increases. Conversely, a negative β value (closer to -1) indicates a negative relationship, where an increase in the independent variable leads to a decrease in the dependent variable. By interpreting both the p-value and the β value, the regression weight results offer insights into the strength and direction of the relationships in the model. Among the three of the four newly proposed paths that are significant, H4 (PR → STF) shows a significant negative relationship (β = -0.201), indicating that increased perceived risk reduces satisfaction. H5 (PUF → PCM) demonstrates a strong positive effect (β = 0.766), suggesting that perceived usefulness strongly influences perceived critical mass. H7 (PCM → CTA) is also significant (β = 0.424), indicating that perceived critical mass positively affects continuance intention. In addition to these newly proposed paths, the rest of the hypotheses (H1, H2, H3, and H6) are also significant and show positive relationships.

Table 4. The regression weight of Hypotheses

Hypotheses	Paths			beta (β)	P-value	Results
H1	CNF	→	PUF	.663	***	Significant
H2	CNF	→	STF	.209	***	Significant
H3	PUF	→	STF	.452	***	Significant
H4	PR	→	STF	-.201	***	Significant
H5	PUF	→	PCM	.766	***	Significant
H6	STF	→	CTA	.541	***	Significant
H7	PCM	→	CTA	.424	***	Significant
H8	PR	→	CTA	.063	**.235**	**Not Significant**

Note: PUF= Perceived Usefulness, CNF= Confirmation, STF= Satisfaction, CTA= Continuance Intention, PR= Perceived Risk, PCM= Perceived Critical Mass.

The R-square value is also a crucial step in the structural model evaluation stage. It indicates the extent to which the independent variables (exogenous constructs) explain the variability in the dependent variables (endogenous constructs) [66]. The R-square results help assess whether the structure formed by the hypotheses supports the proposed theoretical model. The R-square values are classified into three levels [59]: (1) High value (between 0.50 and 1.00), indicating that the model explains more than half of the variance in the dependent variable, which is generally considered good for practical applications; (2) Moderate value (between 0.25 and 0.49), where the model explains part of the data variability and still provides important insights, especially in research involving user behaviour, where external factors are difficult to measure accurately; and (3) Low value (below 0.25), indicating that the model poorly explains the data variance and

may require the addition of exogenous variables or modifications to the model paths. In this study, it is shown that 3 out of 4 endogenous constructs (PCM with 0.677, STF with 0.641, and CTA with 0.873) fall into the "High" category, while PUF with 0.408 falls into the "Moderate" category. Based on these results, the paths formed from the hypotheses in this study support the proposed theoretical model, with the R-square results indicating a sufficient level of fit in explaining the variance between constructs.

4.3. Discussion

The results demonstrate that confirmation positively influences perceived usefulness (H1), consistent with the ECM framework. which asserts that confirmed expectations enhance perceived usefulness. The research highlights that when users' initial expectations align with their actual experiences, their perception of a technology's utility strengthens. For example, in the context of e-wallets, confirmation significantly impacts perceived usefulness by fostering confidence in the platform's reliability and efficiency [27]. In the context of food merchants, the alignment between initial expectations and the actual utility of OFD services ensures smoother operations and improved customer reach, creating tangible business benefits that amplify the perception of usefulness. These findings emphasize the importance for OFD providers to maintain consistent service quality and clear communication to meet merchants' expectations, thereby reinforcing perceived usefulness. For the second hypothesis (H2), which posits that confirmation positively influences satisfaction, the findings are consistent with previous studies validating ECM's applicability across various technological domains. Research shows that when expectations are fulfilled during a user's interaction with a service or system, satisfaction naturally increases [29]. In mobile application contexts, for instance, confirmation fosters satisfaction by affirming the anticipated performance. This finding highlights the importance for OFD providers to clearly communicate their service capabilities and consistently deliver on promised operational benefits. By doing so, providers can foster greater satisfaction and strengthen trust among merchants. This sense of alignment between expectations and outcomes strengthens their trust in the platform, affirming the essential role of expectation confirmation in building satisfaction. The results also reveal that perceived usefulness positively influences satisfaction (H3), a finding that resonates with the foundational principles of ECM. Perceived usefulness, reflecting the degree to which a system enhances user performance, has consistently been shown to correlate strongly with satisfaction. For instance, research in financial information systems has demonstrated that users derive satisfaction from systems that improve efficiency and productivity [31]. In this study, food merchants who leverage OFD platforms to optimize delivery logistics and increase order accuracy are likely to experience higher satisfaction, as the system aligns directly with their operational goals. These results align with previous research, reaffirming the importance of aligning system functionality with user needs to foster satisfaction. This suggests that OFD providers must continuously innovate features that directly enhance merchants' operational success, such as tools for managing orders or analyzing customer trends.

The study's findings also indicate that perceived risk negatively influences satisfaction (H4), echoing existing literature on the detrimental effects of uncertainty on user experience. Perceived risk encompasses concerns related to financial, privacy, and performance uncertainties. Prior study, such as those examining online shopping in emerging economies, have shown that higher perceived risks—such as transaction security or product reliability concerns—significantly reduce user satisfaction [67]. This research extends these insights by focusing on food merchants, whose satisfaction is adversely impacted by concerns over financial fraud, data breaches, or unresolved transaction errors within OFD platforms. Addressing these perceived risks is crucial to improving merchant satisfaction, particularly in the post-pandemic. This highlights the urgent need for OFD providers to implement robust safeguards to maintain merchant confidence. In addition, the findings indicate that perceived usefulness has a significant positive impact on perceived critical mass (H5), aligning with established theories in technology acceptance. When users perceive a system as useful, they are more likely to adopt and recommend it, contributing to its critical mass. The study on mobile health communication tools demonstrate that perceived usefulness significantly influences perceived critical mass by encouraging broader adoption among users [68]. When food merchants perceive OFD platforms as beneficial, they not only continue using the system but also indirectly contribute to its growth by encouraging other merchants to adopt it. This self-reinforcing cycle is critical for achieving and sustaining critical mass. In terms of satisfaction positively influences continuance intention (H6), the results confirm that higher satisfaction levels significantly enhance the likelihood of continued platform usage. Previous study, those focusing on AI-based applications, have shown that satisfaction drives continued engagement when the platform aligns with user expectations and delivers tangible benefits [69].

For OFD services, satisfaction encompasses merchants' reflections on their decision to adopt the platform and their overall experiences with it. For example, merchants who consistently experience timely deliveries, accurate payment processing, and effective customer support are more likely to maintain their engagement with OFD services. The findings underscore the necessity for OFD providers to consistently deliver high-quality services that meet merchants' evolving needs. Finally, the study finds that perceived critical mass positively influences continuance intention to use OFD services (H7). Research on groupware technologies demonstrates that perceived critical mass significantly impacts adoption and sustained use, as users prefer to align with widely adopted platforms [68]. In this study, critical mass is

defined as a condition where widespread usage among merchants and customers creates a compelling incentive to remain engaged. Food merchants who view OFD services as essential for staying competitive feel obligated to continue using the platform to avoid missing out on market opportunities. This result underscores the importance of achieving and sustaining critical mass to drive long-term engagement, particularly as the pandemic transitions to an endemic phase. Given the specific platform maturity stage during data collection, this finding reflects the specific context of platform maturity and market penetration during the time of data collection. This period marks the peak of platform penetration since the platform's initial launch, with the highest popularity in food industries, as highlighted in the introductory section.

For the insignificant relationship, H8 proposed that perceived risk would negatively impact continuance intention, but the relationship was found to be statistically insignificant. In the case of Indonesian merchants, the insignificance of the path in H8 might also occur in other countries or regions with similar characteristics, particularly when focusing on the time horizon during the transition to a post-pandemic period. For example, during the COVID-19 pandemic, perceived risk did not significantly influence users' continuance intention for online shopping [69]. One explanation for this is that merchants prioritize operational benefits and market reach over perceived risks. This suggests that while risks are present, the overall value offered by online shopping outweighs these concerns. Moreover, another study has shown that the effect of perceived risk on continuance intention can be mediated by other factors, such as satisfaction. For instance, satisfaction significantly mediates the relationship between perceived risk (specifically COVID-19 perceived risk) and students' continuance intention to use e-learning systems [70]. Although perceived risk might initially discourage usage, users' satisfaction with their e-learning experience can counterbalance this, positively influencing their intention to continue using the system. Delving into this case study, food merchants similarly tend to overlook risks due to the perceived operational maturity of online food delivery (OFD) providers. Even when risks are acknowledged, many merchants continue using OFD platforms because of the tangible benefits they experience, such as improved operational efficiency and expanded market access. Therefore, perceived risk indirectly influences continuance intention, with satisfaction acting as a mediator. This highlights the complex interplay of factors driving the continued use of OFD services.

4.4. Implication

This study extends the existing literature on the ECM by examining the continuance intention of merchants using OFD services, a relatively underexplored area compared to the food buyer's perspective. Academically, it deepens the understanding of how post-pandemic shifts in merchants' confirmation, as an initial factor, influence the continued adoption of OFD services. The inclusion of constructs such as perceived critical mass and perceived risk broadens the perspective on factors affecting continuance intention within the OFD context. Additionally, the study finds that H8, which hypothesized that perceived risk negatively impacts continuance intention, is statistically insignificant. This suggests that perceived risk does not strongly deter merchants from continuing to use OFD services. The findings also underscore the flexibility of ECM in adapting to diverse contexts, such as the food delivery industry, highlighting its relevance for analyzing various technological adoption scenarios.

From a practical standpoint, especially for OFD providers and merchants, the findings offer actionable insights. The significance of perceived usefulness, satisfaction, and critical mass highlights the need to continually enhance platforms to meet merchant expectations. Ensuring system reliability and utility is critical for maintaining merchant engagement. Service providers should prioritize improving ease of use, reducing transactional errors, and addressing potential risks, as these factors significantly influence merchant satisfaction and, consequently, continuance intention. Furthermore, perceived critical mass is pivotal in sustaining merchant participation, emphasizing the importance of community-building initiatives to attract more merchants and customers to the platform. By effectively managing and mitigating perceived risks—such as transaction security and compensation concerns—OFD providers can minimize negative impacts on satisfaction, fostering long-term usage by merchants.

5. Conclusion

This study addresses a critical gap in Online Food Delivery (OFD) research, which has historically focused predominantly on food consumer behavior while neglecting the perspectives of other end user, food merchants. To bridge this gap, it investigates the factors influencing merchants' continuance intention to adopt OFD platforms in the post-pandemic landscape. This study provides a comprehensive examination of the factors influencing merchants' continuance intention to use OFD services in the post-pandemic context, guided by the Expectation-Confirmation Model (ECM). The findings confirm the significant roles of confirmation, perceived usefulness, and satisfaction as core ECM constructs, while introducing perceived critical mass and perceived risk as extended factors tailored to the unique dynamics of the OFD ecosystem. Data analysis revealed that satisfaction strongly predicts continuance intention, emphasizing the necessity of delivering reliable and beneficial OFD services. Perceived critical mass also emerged as a key determinant, demonstrating the OFD platform's value when widely adopted. Additionally, perceived risk indirectly influences continuance intention through satisfaction, illustrating that while risks such as financial fraud and operational

errors may affect user experiences, the perceived benefits of OFD services often outweigh these concerns. Refinements in the measurement model strengthened the structural validity of the analysis, ensuring that the relationships among constructs accurately reflected merchant perceptions. This was particularly significant in capturing the evolving dynamics of the post-pandemic environment, where digital platforms like OFD have transitioned from a necessity to a competitive advantage for merchants. The role of perceived critical mass underscores the importance of fostering widespread adoption and engagement to sustain long-term platform success. By extending the ECM framework with perceived critical mass and perceived risk, this research offers a nuanced understanding of the factors driving merchant engagement with OFD.

There are several avenues for future research to expand on these findings. First, while this study focuses on merchants in Indonesia, future studies could explore how these factors play out in other countries or regions, where economic and technological conditions might present critical challenges or opportunities. Investigating whether similar patterns of continuance intention emerge in different cultural and regulatory environments could deepen our understanding of the broader OFD ecosystem across environments. The proposed model is robust and adaptable due to its comprehensive development, reflecting standardized collaboration schemes between OFD providers and food merchants, ensuring adaptability across contexts. As many OFD providers are already multinational companies operating their business (cross-developing and/or developed countries), and global pandemic responses have shared similarities, the model's relevance extends beyond the studied context. Future research could test its applicability in comparable markets, validating its influence on continuance intention across different environments. Moreover, future research could shift the perspective from food merchants to other users in the OFD ecosystem, such as delivery drivers. Drivers represent a crucial component in ensuring the success of OFD platforms, but their experiences and factors influencing their continuance intention remain underexplored. Drivers face unique risks related to job security, compensation, and safety, which may impact their satisfaction and willingness to continue working with OFD services. By exploring drivers' continuance intention, future studies could offer a more holistic view of the OFD ecosystem, balancing the experiences of food buyers, merchants, and delivery drivers. By broadening the scope of research to include different countries, user groups, and perspectives, future studies can help identify new strategies in online food delivery industries.

6. Declarations

6.1. Author Contributions

Conceptualization, R.Y. and B.T.; methodology, R.Y. and B.T.; formal analysis, R.Y.; investigation, R.Y.; data curation, R.Y.; writing—original draft preparation, R.Y. and B.T.; writing—review and editing, R.Y. and B.T.; visualization, R.Y.; supervision, B.T. All authors have read and agreed to the published version of the manuscript.

6.2. Data Availability Statement

The data presented in this study are available in the article.

6.3. Funding

6.4. Institutional Review Board Statement

Not applicable.

6.5. Informed Consent Statement

Not applicable.

6.6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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