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AN ANALYSIS OF CUSTOMER ATTITUDES TOWARDS TECHNOLOGY DRIVEN PRODUCTS: A CASE STUDY IN THE RETAIL INDUSTRY

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To my father and mother

Egemen Hopalı

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TABLE OF CONTENT

ACKNOWLEDGEMENT i
TABLE OF CONTENT ii
ÖZET iii
ABSTRACT iv
CLAIM OF ORIGINALITY v
SYMBOLS vi
ABBREVIATIONS vii
LIST OF FIGURES viii
LIST OF TABLES ix
1. INTRODUCTION 1
2. LITERATURE REVIEW 9
2.1. Fintech Usage in the Retail 9
2.2. Mobile Wallets 18
2.2.1. Survey Analysis and Statistics 22
2.2.2. A Comprehensive Literature Review of Mobile Wallets 26
2.3. Technology Acceptance Theories and Models 42
2.3.1. Diffusion of Innovation Theories 42
2.3.2. Theory of Reasoned Action and Theory of Planned Behavior 45
2.3.3. Technology Acceptance Model 48
2.3.4. The Unified Theory of Acceptance and Use of Technology 51
2.3.5. Technology Readiness Index 57
3. PROPOSED MODEL 60
4. METHODOLOGY 70
5. DATA ANALYSIS AND RESULTS 77
6. DISCUSSION 94
7. CONCLUSION 99
REFERENCES 102
APPENDIX 136
RESUME 138

ÖZET

TEKNOLOJİ ODAKLI ÜRÜNLERE YÖNELİK MÜŞTERİ TUTUMLARININ ANALİZİ: PERAKENDE SEKTÖRÜNDE BİR UYGULAMA

Bugünün hızla gelişen dünyasında, işletmeler teknoloji odaklı müşterilerin ihtiyaçlarına uyum sağlamalıdır. Bu tez, müşterilerin teknolojiyle yönlendirilen ürünlere olan tutumlarını araştırmakta olup özellikle akıllı perakende teknolojilerinde mobil cüzdan üzerinde odaklanmaktadır. Çalışma, müşteri algıları ve davranışı üzerinde mobil cüzdanların etkisini analiz etmek için Yapısal Eşitlik Modellemesi (SEM) yöntemini ve SPSS AMOS programını kullanmıştır. Bulgular, faydacı ve hazcı motivasyonların rollerini ve güvenin müşteri tutumları üzerindeki olumlu etkisini vurgulamaktadır. Bu motivasyonları anlamak, güvenin önemini tanımak ve güvenli ve güvenilir çözümlerin gerekliliğini vurgulamak, teknolojiyle yönlendirilen ürünlere ilişkin müşteri tutumlarının kapsamlı bir şekilde incelenmesi için önemlidir.

Teknoloji Hazır Olma ve Kabul Modeli'ne (TRAM) dayanan önerilen model, teknolojiyle yönlendirilen ürünlerin faydacı ve hazcı yönlerine ilişkin müşteri beklentilerine ışık tutmaktadır. İşlem hızı ve güveni dikkate alarak, model müşteri tercihleri ve davranışlarına holistik bir bakış sunar. Çalışma, işlem hızının kullanım kolaylığını artırdığını ortaya koymakta ve iyimserlik, yenilikçilik ve rahatsızlık gibi faktörlerin kullanım kolaylığı ve algılanan faydalılığı önemli ölçüde etkilediğini göstermektedir. Bu bulgular, ürün performansının optimize edilmesini ve teknolojiyle yönlendirilen ürünlerin tasarımı ve uygulanmasında faktörlerin dikkate alınmasını vurgulamaktadır. Araştırma, işletmelerin müşteri tutumlarını daha iyi anlamalarını ve stratejilerini buna göre uyarlamalarını sağlayarak, teknolojiyle yönlendirilen ürünlerin dinamik ortamında müşteri memnuniyetini ve başarısını artırmaya yönelik değerli içgörüler sunmaktadır.

ABSTRACT

AN ANALYSIS OF CUSTOMER ATTITUDES TOWARDS TECHNOLOGY DRIVEN PRODUCTS: A CASE STUDY IN THE RETAIL INDUSTRY

In today's rapidly evolving world, businesses must cater to the needs of technology-oriented customers. This thesis investigates customer attitudes towards technology-driven products, specifically focusing on the mobile wallet in smart retail technologies. The study employed Structural Equation Modeling (SEM) methodology with SPSS AMOS to analyze the impact of mobile wallets on customer perceptions and behavior. The findings highlight the roles of utilitarian and hedonic motivations and the positive influence of trust on customer attitudes. Understanding these motivations is crucial for comprehensively studying customer attitudes towards technology-driven products while recognizing the significance of trust and emphasizing the need for secure and reliable solutions.

Based on the Technology Readiness and Acceptance Model (TRAM), the proposed model offers insights into customer expectations regarding utilitarian and hedonic aspects of technology-driven products. Considering transaction speed and trust, the model provides a holistic view of customer preferences and behaviors. The study reveals that transaction speed enhances perceived ease of use, and factors like optimism, innovativeness, and discomfort significantly influence perceived ease of use and perceived usefulness. These findings emphasize optimizing product performance and considering factors during the design and implementation of technology-driven products. The research contributes valuable insights, enabling businesses to understand customer attitudes better and tailor their strategies accordingly, ultimately improving customer satisfaction and success in the dynamic landscape of technology-driven products.

CLAIM OF ORIGINALITY

AN ANALYSIS OF CUSTOMER ATTITUDES TOWARDS TECHNOLOGY DRIVEN PRODUCTS: A CASE STUDY IN THE RETAIL INDUSTRY

This thesis investigates customer attitudes towards technology-driven products, specifically focusing on the mobile wallet in smart retail technologies. In today's rapidly evolving world, businesses must cater to the needs of technology-oriented customers. By accurately identifying these customers and optimizing service designs, companies gain a competitive advantage, enhance customer acquisition, and foster engagement, especially in the competitive retail industry.

The study investigates the transformative impact of Industry 4.0 and its components, like IoT, robotics, cloud computing, AI, and machine learning, on the products used in the retail sector. Customers now widely integrate technology into their purchasing processes. This thesis highlights the importance of secure, fast, sustainable, and accessible technology-driven products through successful service design, enabling new business models and customer acquisition, ultimately enhancing customer experiences and competitive positioning. Using Structural Equation Modeling (SEM) and the Technology Readiness and Acceptance Model (TRAM), the proposed model offers unique insights into customer expectations, perceptions, and behaviors regarding technology-driven products.

This thesis significantly enhances our understanding of customer attitudes towards technology-driven products. The study emphasizes the roles of utilitarian and hedonic motivations and the positive influence of trust on customer attitudes. Findings also reveal the impact of transaction speed on perceived ease of use and the significant effects of optimism, innovativeness, and discomfort on perceived usefulness. By emphasizing the importance of meeting customer needs, this study offers valuable insights that empower retailers to gain a deeper understanding of customer attitudes, optimize product performance, and tailor strategies accordingly. The findings presented in this thesis provide actionable suggestions for retailers to enhance customer satisfaction and achieve success in the dynamic landscape of technology-driven products.

SYMBOLS

N : Overall Sample Size

X^2 : Chi-Square

F_k : Minimum Fit Function

k : Number of Estimated Parameters

S : Observed Covariance Matrice

$\sum_k$: Estimated Covariance Matrice

ABBREVIATIONS

DoI : Diffusion of Innovation

TRA : Theory of Reasoned Action

TPB : Theory of Planned Behavior

TAM : Technology Acceptance Model

UTAUT : The Unified Theory of Acceptance and Use of Technology

TRI : Technology Readiness Index

TRAM : Technology Readiness and Acceptance Model

CMIN / df : Chi-Square / Degrees of Freedom

AGFI : Modified Goodness of Fit Index

GFI : Goodness of Fit Index

CFI : Comparative Fit Index

IFI : Increasing Fit Index

NFI : Normed Fit Index

PNFI : Parsimony Normed Fit Index

SEM : Structural Equation Modeling

TLI : Tucker Lewis Index

RMSEA : Root Mean Squared Error of Approximation

LIST OF FIGURES

Figure 1.1 Fintech business models in the retail 14
Figure 1.2 Fintech products in the retail 17
Figure 2.1 Survey method 23
Figure 2.2 Publication by years 24
Figure 2.3 The mapping of the academic research database about mobile wallets 25
Figure 2.4 Research topics 26
Figure 2.5 DoI model 43
Figure 2.6 TRA model 45
Figure 2.7 TPB model 46
Figure 2.8 The Technology Acceptance Model 49
Figure 2.9 UTAUT model 52
Figure 2.10 UTAUT 2 model 55
Figure 2.11 TRI model 57
Figure 2.12 TRAM model 59
Figure 3.1 Proposed model 60
Figure 5.1 Number of the participant's genders 80
Figure 5.2 Rates of age groups. 80
Figure 5.3 Customer education rates 81
Figure 5.4 Time of use rates 81
Figure 5.5 Graph of the mean of latent variables 82
Figure 5.6 Path Analysis of the proposed model in AMOS 90
Figure 5.7 Standardized model with path coefficients 92

LIST OF TABLES

Table 4.1 SEM fit indices 74
Table 5.1 Demographic measurement details of survey participants 77
Table 5.2 Demographic details of the pilot test participants 78
Table 5.3 Cronbach's Alpha Coefficient of the pilot test 79
Table 5.4 Demographic details of the survey 79
Table 5.5 Cronbach's Alpha Coefficient of survey factors 82
Table 5.6 Pearson Correlations: Transaction Speed 83
Table 5.7 Pearson Correlations: Optimism 83
Table 5.8 Pearson Correlations: Discomfort 84
Table 5.9 Pearson Correlations: Innovativeness 84
Table 5.10 Pearson Correlations: Trust 84
Table 5.11 Pearson Correlations: Perceived Usefulness 85
Table 5.12 Pearson Correlations: Perceived Enjoyment 85
Table 5.13 Pearson Correlations: Perceived Ease of Use 85
Table 5.14 Pearson Correlations: Attitude 86
Table 5.15 Pearson Correlations: Intention to Use 86
Table 5.16 Factor loadings 87
Table 5.17 Factor loadings 2nd iteration 88
Table 5.18 CR and AVE results of factors 89
Table 5.19 Interconstruct correlations 89
Table 5.20 Summary of hypotheses testing results 91
Table 5.21 Model fit summary 93

1. INTRODUCTION

Over the last decade, the diversity and speed of technology-enabled innovations have accelerated. The contribution of the ease of access to the internet in this situation cannot be denied. According to the World Bank (2021), 92 percent of the world's population lived within the 3G signal range in 2018. This rate was 80 percent for 4G technology access, which provides faster internet with 400 megabytes per second and requires smartphone applications. In the recent commercial launch of 5G technology, the speed rises to 1000 megabytes per second.

In today's world, where technology and innovation are constantly developing, it has become extremely vital to understand technology-oriented customers and offer them the products and processes to experience technological innovation. Companies are expected to make valid identification of technology-oriented customers and optimize the service designs of the products to be presented. This way, companies can provide a competitive advantage, customer acquisition, and customer engagement. Especially in competitive industries such as retail, this notion is two times more important. In the retail industry, where competition is experienced on a high level, companies must fulfill the customer needs fastly, aside from offering innovative products with an accurate service design to take an advantageous position against their competitors.

Along with the occurrence of Industry 4.0 and its components, the development of intelligent systems and widespread use of mobile devices and the Internet; pave the way for retailing customers to use technology commonly in their purchasing processes. The components of Industry 4.0, such as the Internet of Things (IoT), robotics, cloud computing, artificial intelligence (AI), and machine learning, facilitate the integration of innovative products and complex processes into the retail industry. Unmanned shopping stores, financial technology (FinTech), and chatbots offering solutions via machine learning; provide opportunities for new business models and customer acquisition for the retail industry. In this ecosystem that technological innovation has created for retailing, offering secure, fast, and accessible products through a successful service design is essential for increasing customer experience and competitive positioning.

Retailers seek innovative ways to integrate more customer-centric products into their

service to provide customer acquisition and customer engagement (Pillai et al., 2020; Anderson et al., 2007; Han et al., 2014). Riegger et al. (2021) refer to consumer reactions to technology-enabled personalization in the retail industry and suggest a model for the success of this new phenomenon. According to the model, the retailer needs to comfort with five distinct drivers (control, hedonic, interaction, integration, and utilitarian) and handle four distinct barriers (exploitation, misfit, interaction, and lack of confidence). Alexander & Kent (2020) demonstrate that implementing and integrating innovative store technology improves customer experience. Researchers suggest two models test this hypothesis. Models validate that technology enables customer shopping journeys and induces customer experience in stores. Technology and the voice of customers shape business model innovation and service innovation. In parallel, innovative technologies have transformed customer experience through IoT, AI, Virtual Reality (VR), Augmented Reality (AR), robots, chatbots, and virtual assistants (Keiningham et al., 2020; Hoyer et al., 2020).

Technology acceptance of consumers is needed to measure to provide sustainability of business models and understand shopping behaviors. If the main innovation drivers in retailing reveal, retailers can optimize Service Design (SD) and improve User Experience (UX). Understanding consumer acceptance criteria enables the retailer to predict future market trends and present innovative products, hence making extensive usage (Pantano, 2014; Xu et al., 2020). Technology Acceptance Model (TAM) is extensively used to measure consumer perception and experiences. It is based on four main constructs: perceived ease of use, perceived usefulness, attitude, and behavioral intention (Pookulangara & Koesler, 2011; Gursoy et al., 2019). Rese et al. (2017) have employed TAM to show how customers accept augmented reality apps. The results have demonstrated that different AR apps' relative importance of perceived enjoyment and perceived informativeness varies. Pantano et al. (2017) developed a new conceptual model based on TAM with new constructs such as quality of information, interactivity, response time, and aesthetic quality. Model tests the new technology usage through virtual try-on for online purchase. Smart Retail Technology (SRT) delivers customer service via a network of intelligent systems (Wünderlich et al., 2015; Willems et al., 2017). Customer adoption of SRT and resistance factors to SRT investigates through TAM, system characteristics, and technology readiness (Roy et al., 2018). The Unified

Theory of Acceptance and Use of Technology (UTAUT) also aims to explain customer intentions as an acceptance model. It is based on four constructs: performance expectancy, effort expectancy, facilitating conditions, and social influence (Venkatesh et al., 2003). Zhou et al. (2019) employ extended TAM and UTAUT models to find out factors influencing behavior intentions of telehealth. UTAUT verifies mobile payment services adoption conditions and tries to facilitate customer adoption by presenting an understanding of perceived trust, security, and risk (Slade et al., 2015; Park et al., 2019).

State-of-the-art Industry 4.0 technologies accelerate smart retail technology. As the last industrial revolution, Industry 4.0 helps interconnect intelligent objects and virtualization (Machkour & Abriane, 2020; Hopalı & Vayvay, 2018). Components of Industry 4.0, such as the IoT, robotics, cloud computing, AI, and cyber security, bring about success over complex processes and product differentiation in the retail industry. Real-time data from the environment and retail products need smart sensors, seamless integration, and reliable communication to use store IoT applications (Aheleroff, et al., 2020; Van Geest et al., 2021). IoT and Industry 4.0 enable retailers to build self-check systems and unmanned stores where resources and entities interact with each other in the stores (Vallandingham et al., 2018; Liu et al., 2018). In addition, blockchain technology removes the privacy risks of IoT and security vulnerabilities. The retailer can trace foods through the transaction system of blockchain and know who the supplier's trade with (Wang et al., 2020). Retail companies should use cloud-based big data analytics systems in the new era of Industry 4.0 to uncover hidden patterns and understand customer behavior (Gill et al., 2019; Zhang et al., 2019). In addition to these, AI and machine learning algorithms enable retailers to learn customer behavior via chatbots which can be competent at acting as emotional partners. Thus, chatbots can be effective during customer decision-making (Luo et al., 2019; Heo & Lee, 2018). Smartphone penetration, mobile payment infrastructure, and widespread internet adoption have enhanced customer experiences. Mobile shopping apps offer tailored shopping experiences by increasing omnichannel capabilities and integrating user-friendly features. Also, IoT usage relies on customer smartphones. As a mobile payment method, the wireless network tracks customers during store visits (Chopdar & Balakrishnan, 2020; Jocevski et al., 2020).

Machine learning algorithms are a recently developing phenomenon that especially technology-oriented products benefit from and add to their service design. Machine

learning refers to the system's ability which learns automatically and improves from experience. It is a subset of one of the Industry 4.0 components, AI. Machine learning progressively gains a broader impact on many industries and decision-making systems. Thus, this state-of-the-art technique also presents a broad research interest for retailers (Brik et al., 2019). Machine learning algorithms enable systems to make estimations with data interpretation and take resolutions with their autonomous, adaptable structure. Through the use of machine learning algorithms, decision support systems improve the products which utilize the former characteristics of products (Dalzochio et al., 2020; Cachada et al., 2018).

Moreover, machine learning enables product designers to estimate the lifetime of a product by training a learning algorithm based on a large amount of data (Schmidt & Wang, 2018; Wang & Wang, 2017). Different input data can be applied to train the machine learning algorithm. Input data can be gathered as video, textual, or sensor. Also, the input data acquisition approach could be real-time or a mix of real-time and historical. According to Hedge & Rokseth (2020), learning can be classified as learning from textual, numerical, and state-of-the-art data. Machine learning algorithms such as artificial neural network (ANN), support vector machine (SVM), decision tree (DT), latent dirichlet allocation (LDA), radial basis function (RBF), latent semantic analysis (LSA), natural language processing (NLP), random forests (RF), stochastic gradient tree boosting (SGTB) are convenient for prediction by processing information rich textual data. Tixier et al. (2016) propose an NLP model to handle the accident coding process of unstructured textual reports. Content mining combined with NLP is used for customer churn prediction based on unstructured data, and the results are auspicious (Sun et al., 2017). SGTB and RF are applied to a large pool of textual accident data (Tixier et al., 2016). Ladyzinski et al. (2019) conduct RF and Deep Neural Networks to identify customer interest in credit products. Paolanti et al. (2019) propose a model for robotic retail surveying by deep learning textual and visual data to improve retail stores' overall performance. Extracted textual data and visual image features have been trained by six machine learning algorithms, Naive Bayes (NB), k-Nearest Neighbor (kNN) SVM, DT, RF, and ANN. By processing numerical data, machine learning algorithms can provide profound insights into different factors and customer purchase behaviors. SVM-based machine learning algorithm uses an imbalanced data set of credit card customers to forecast the client churn

(Farquad et al., 2014). Tree-based algorithms are used to predict the behaviors of electronic banking customers (Keramati et al., 2016). Huber & Stuckenschmidt (2020) apply to feed-forward ANNs (FANN), recurrent neural networks (RNNs), and gradient-boosted regression trees (GBRT) to forecast daily retail demand. Generative adversarial networks (GAN) employs to generate clothing images for pattern makers in the fashion retail industry (Kato et al., 2019). Machine learning algorithms such as AdaBoost, Naïve Bayesian, RIPPER, and C4.5 analyze house sales based on housing data (Park & Bae, 2015). Loureiro et al. (2018) employ DT, RF, ANN, SVM, and Linear Regression to compare sales prediction in the fashion retail industry. According to the results, RF performs significantly better than other algorithms.

Market basket analysis is one of the practical machine learning methods in the retail industry that defines an association between products. Market basket analysis is a crucial component of analytical CRM in retail organizations. Retail data can be analyzed not only with customer-level sales data but also basket-level data can be analyzed in order to produce groups of customer visits based on the product categories (Svetina & Zupancic, 2005). Thanks to the combinations that can be beneficial for shelf design and promotion of products, this type of segmentation can identify customer shopping intention, setting associations between the products purchased during a customer's visit (Cil, 2012; Chen et al., 2005; Kim et al., 2012). By using the data mining technique, identifying the process of related products bought together in one transaction can be managed, Surjandari & Seruni (2010) have chosen Apriori Algorithms as a method of data mining process & has implemented WEKA data mining software in order to make market basket analysis; so that association rule between products was shown. Videla-Cavieres & Rios (2014) indicate that meaningless relationships can be found when enormous amounts of scattered data are processed through market basket analysis techniques. Graph mining techniques are developed based on market basket analysis to group wholesale and retail supermarket chain customers. Boztuğ & Reutterer (2008) present a data-driven approach for basket selection via a multi-category choice model to understand customer heterogeneity and design target marketing promotions. Apriori and PRIM algorithms are implemented to account for association rules in a real-world retail data set so that a supervised learning approach is discussed and identified in market basket analysis (Kronberger & Affenzeller, 2011). Association rules mining is not always the best method for analyzing market basket

data because the data matrix is usually large and sparse. Avoiding the sluggish generation of trivial rules, Tan & Lau (2014) offer time series clustering instead of association rule mining on massive sales transaction data. Due to the enormous amount of data acquired from data warehouse channels of retail organizations, the well-known sequential Apriori Algorithm is not always suitable to analyze. The grid-based rule mining algorithm is offered instead of Apriori Algorithm for market basket analysis in the retail sector (Singh et al., 2007).

Chiang & Yang (2018) predict potential customer lifetime value (CLV) in retail through segmentation generated with data mining to present customer personality traits concerning the country of origin and brand personality. According to Phan & Vogel (2010), CRM systems with business analytics increase satisfaction and customer relations in the retail industry; while investigating successes and failures of Fingerhut company researchers indicate that critical factors such as CRM used to handle problematic accounts, Business Intelligence used to tailor ability to buy are highly effective. Ramageri & Desai (2013) present consumer behavior using a recency, frequency, and monetary (RFM) model in a retailer and then evaluate a proposed segmented customer model by CLV. Differences in retail store choice behavior of customers are investigated in the Malaysian retail industry for the purchase of fresh meat and fresh fruit and vegetables through segmentation (Chamhuri & Batt, 2013). Israeli mall customers are segmented by a two-step cluster analysis, including the hierarchical analysis method of Ward with the non-hierarchical K-means clustering technique (Gilboa, 2009). Data mining combining the fuzzy RFM model with fuzzy c-means and fuzzy subtractive model is conducted in a retail company. The results are present. Fuzzy c-means have higher validity than a subtractive algorithm for segmentation (Nugraheni, 2013).

Big data analytics is an effective technique to analyze customer behavior and transform it into valuable outcomes. Customer micro-segmentation, in-store behavior analysis, and price optimization are the main gains of big data analytics. High volumes of customer data from various sources, such as receipt data and loyalty programs, are provided in retail organizations. Big data analytics enable retailers to analyze customer data, and micro-segmentation can be done. Customer behavior analytics and micro-segmentation are still unexplored markets. Big data analytics can provide a better advancement for this market (Kaisler et al., 2013; Provost & Fawcett, 2013; Michael & Miller, 2013). Khade (2016)

claims a proposed Map Reduced implementation through the C4.5 decision tree algorithm to perform customer behavior analyses. Verma & Singh (2017) developed a new approach to big data analytics for retail organizations using Map Reduced-based Apriori algorithm and Hadoop-based intelligent cloud architecture. Lee (2017) presents a GA-based model for big data analytics to support anticipatory shipping in retail by deploying cloud computing to store big data generated from different channels. Jiang & Leung (2015) propose a big data analytic algorithm to analyze big uncertain data using the Map Reduce model on a cloud environment for a shopper market basket.

Adopting mobile phones, online channels, and data connections pushes brick-and-mortar businesses to employ AI. AI is conducted in the retail industry through three significant AI approaches Neural Networks, Genetic Algorithms, and Fuzzy Logic (Hou & Chen, 2011; Chen & Ou, 2011; Popescu, 2018). Choi et al. (2015) proposed an item-level RFID to enhance the shopping experience by capturing customer shopping preferences in a retail company. Cruz et al. (2019) combine state-of-the-art AI techniques, deep learning, and augmented reality to guide customers toward specific products in large retail stores. Ciabattoni et al. (2017) proposed a multitasking MultiKernel learning approach for measuring emotional customer experience. Gao et al. (2009) rearranged Holt-Winters' model and created a neural network-based forecasting algorithm to provide valuable customer insights for retailers. RFID is employed for positioning customer shopping baskets through shopping path tracking in the retail environment (Vukovic et al., 2012).

This study is dedicated to identifying customers' innovative product use and retailers' product features to offer to technology-driven customers. During the study, smart retail technologies were researched, and the factors affecting customers' shopping intentions were determined through technology acceptance models. Smart technologies used by technology-oriented customers in retail have increased their frequency of use and customer interest in recent years. In particular, developments in smart technologies such as chatbots, unmanned stores, blockchain applications, and Fintech products are met with interest among customers. However, these technological products, which are still very new, should be researched and understood in depth to determine customers' shopping intentions, identify the development points for service providers, and improve the customer experience in retails.

For this reason, Fintech, one of the smart retail technologies, was used to identify the shopping intentions of technology-oriented customers. Fintech products were examined in the literature review section, and mobile wallets were chosen to carry out detailed studies on the application and correctly determine the research area. The literature on mobile wallets, one of the Fintech products, was examined in this study in detail. Mobile wallets, which are highly new and developing products, have a history of only ten years. They are traceable and innovative products that are increasingly popular with the widespread use of smartphones. As an application, the mobile wallet data of a retailer in online and offline channels were analyzed with the help of a proposed technology acceptance model. Thus, the factors affecting the shopping intention of technology-focused customers were explained. Furthermore, development areas were tried to be determined for merchants and service providers.

The lack of extensive research in the literature on the intention of technology-driven customers to use smart retail technology products has led to this thesis. For this purpose, mobile wallet literature research was conducted, and articles published on Scopus, Web of Science, and Science Direct between 2012 and 2022 were investigated in detail. In addition, technology acceptance models have been scanned in the literature; an originally proposed model was created. The model hypothesis was analyzed thanks to Structural Equation Modeling (SEM). Through this study, mobile wallets, which are smart retail technology products, are grouped in the literature with technology adoption, customer loyalty, competitiveness and security and privacy issues, and customer shopping intentions with the established model are analyzed using retail data. Analyzing mobile wallets, an innovative, sustainable, and ecologically traceable smart retail technology product, to understand technology-oriented customer shopping intention will be beneficial for customer experience and engagement for both merchants and service providers and will open new areas of development. The following section combines a literature review and descriptive statistics categorized by year of publication. Section 3 includes the study's methodology, and section 4 includes the established model analysis and results. The 5th section presents a discussion that covers common findings and outlines the research agenda. In the last section, the study was completed with a conclusion.

2. LITERATURE REVIEW

2.1. Fintech Usage in the Retail

Fintech is a technology-driven innovation that has surfaced in the last decade to transform financial services. It can be defined as a form of alternative finance that is supported by technology. Diverging from traditional finance, Fintech leverages innovative technologies such as artificial intelligence, data science, big data analytics applications, mobile technology infrastructure, internet-based platforms, advanced business operations, and sensors to derive its advantages (Dhanabalan & Sathish, 2018; Mashelkar, 2018). Traditional organizations cannot compete with FinTech services due to reliability and attractiveness. There are two reasons customers and merchants may seek alternative service providers. The first is due to their need for greater trust and confidence in their current providers. The second reason is the emergence of new financial services, including e-insurance, peer-to-peer money transfers, and mobile wallets, which suggest sustainable and state-of-the-art payment options (Chang et al., 2020; Shim & Shim, 2016).

In recent years, technological breakthroughs have enabled merchants to meet customers' demands for payment methods that are speedy, user-friendly, and secure. Traceable, contactless, mobile payment methods have become an increasingly common benefit. Fintech service uses features and products such as Near Field Communication (NFC) tags to the embedded systems, one-click payment, e-insurance, micro-loans, and peer-to-peer money transfers. Indeed, the intensive use of mobile devices and widespread internet access, which have become widespread in recent years, has contributed significantly to this objective. Recent digital transformation efforts have led to the preference for sustainable and innovative payment channels in retail stores. As an inevitable result, Fintech service providers have created a process for integrating digital payment options onto customers' mobile devices to meet the demands of merchants and consumers and provide optimal value.

Fintech revolutionizes the conventional finance model by introducing mobile and digital services. The proliferation of smartphones, the internet, and e-banking has an impact on customers' shopping behaviors. With the help of Information and Communication Technologies (ICT), payment services are evolving and acquiring a more innovative

dimension. Incorporating cloud technology, big data, and social networking services, Fintech provides customer-centric solutions, including mobile payment, crowdfunding, and remittance services. As a result, technology-enabled payment services have expanded traditional finance boundaries and spurred its rapid growth. Competitive financial attractiveness makes Fintech allure to customers and merchants (Brem et al., 2016). Fintech offers development, digitalization, and capitalization processes. Fintech companies relying on automated systems reduce unnecessary operating expenses while improving consumers' operating costs. In addition, Fintech facilitates high-frequency transactions. Customers can easily manage their investments and emerging capital needs through Fintech applications if they have available funds. Another benefit of using Fintech is that companies can gather and analyze large volumes of valuable data sources. The core engineering and technologies behind Fintech come from financial industry experience and strong IT expertise. Data analytics, distributed database, big data analytics, cybersecurity solutions, and cloud technology are leading the new segment of the Fintech ecosystem.

Fintech has emerged as a disruptive force in the retail industry, transforming the way customers interact with financial products and services. Fintech has created several business models that merchants use in their retail stores. Payment processing, mPOS, online marketplaces, lending platforms, and digital wallets are some of the most popular Fintech business models that merchants use to improve their operations, enhance their customer experience, and increase revenue in retail (Figure 1.1). By adopting these models, merchants can stay competitive and meet the changing needs of their customers.

Payment processing is a Fintech business model that merchants use to accept customer payments. This model provides merchants with a payment gateway to process credit and debit card payments. Payment processing enables merchants to accept payments quickly and securely, improving their cash flow and reducing fraud risk.

Research on payment processing in fintech has explored various aspects of the technology, including its adoption by merchants and its impact on the retail industry. Studies have revealed that Fintech payment processing solutions are gaining traction among merchants, particularly small and medium-sized businesses (SMBs). A study by Visa found that 83% of SMBs surveyed in the US were interested in adopting new

payment technologies (Visa, 2019). Another study by Square found that 80% of its US merchants use its payment processing solution (Square, 2018).

A study by the World Bank found that Fintech payment processing solutions can increase financial inclusion by providing access to payment services for unbanked populations (World Bank, 2019). Studies have also found that Fintech payment processing solutions have reduced the costs associated with traditional payment processing methods, such as credit card processing fees (Garg & Kim, 2018). However, some studies have identified several challenges facing Fintech payment processing solutions, including the need to comply with regulatory requirements, the risk of cybersecurity breaches, and the potential for fraud (Adesina, Gupta, & Singh, 2020). Studies have also noted that merchants may face challenges in choosing the right Fintech payment processing solution for their business, as many providers are in the market (Garg & Kim, 2018).

Mobile Point-of-Sale (mPOS) is another Fintech business model that merchants are using in their retail stores. This model allows merchants to accept payments using a mobile device, such as a smartphone or tablet. mPOS systems are easy to use and provide merchants with a cost-effective way to process payments. This model is beneficial for small merchants who need more resources to invest in a traditional point-of-sale system.

Research on mPOS in Fintech has explored various aspects of the technology, including its adoption by merchants, its impact on the retail industry, and the challenges it faces. Studies have found that mPOS devices are gaining popularity among merchants, particularly small businesses. According to a report from Visa (2017), more than half, namely 57%, of the small businesses that were surveyed in the US had already started using mobile payment solutions. Additionally, out of those who had yet to adopt mobile point-of-sale (mPOS), 70% expressed interest in doing so.

Another study by Juniper Research predicted that the number of mPOS devices in use worldwide would reach 54 million by 2021 (Juniper Research, 2017). Research has also revealed that mPOS has disrupted the retail industry by offering retailers a flexible and affordable way to accept card payments. Studies have demonstrated that mPOS has the potential to increase sales for merchants by reducing the number of lost sales due to cash-only transactions (Huang & Shen, 2019). A study by Mastercard found that retailers using mPOS experienced a 25% increase in sales compared to those that did not (Mastercard,

2019). Notwithstanding its potential benefits, mPOS technology poses various challenges, such as ensuring regulatory compliance, mitigating fraud and security breaches, and delivering robust and high-speed connectivity (Kolapo & Adeniran, 2020). In addition, studies have identified that selecting the most suitable mPOS solution for a business may be daunting due to the overwhelming number of service providers in the market (Huang & Shen, 2019).

Online marketplaces are another Fintech business model that merchants are using to expand their sales channels. Online marketplaces provide merchants with a platform to sell their products and services online. These platforms are beneficial for small merchants who need more resources to develop their e-commerce websites. Online marketplaces also give merchants access to a more extensive customer base, which can help them increase their sales.

In the literature, studies have found that online marketplaces have disrupted the retail industry by offering consumers a convenient and efficient way to shop. Online marketplaces enable retailers to reach a wider audience, reduce costs, and increase sales. Research has also shown that online marketplaces have contributed to the growth of the sharing economy, enabling individuals to monetize their assets and skills (Botsman & Rogers, 2010). A study by McKinsey & Company estimated that online marketplaces could account for 40% of the global retail market by 2025 (McKinsey & Company, 2018).

Also, there are various business models used by online marketplaces, including commission-based, subscription-based, and advertising-based models. Commission-based models, where the marketplace takes a percentage of each transaction, are the most common (Katsikeas et al., 2016). Studies have also explored the impact of platform design and features on consumer behavior, such as the use of customer reviews and ratings to build trust and improve purchase decisions (Luo et al., 2019).

On the contrary, some studies identified several challenges facing online marketplaces, including the need to maintain consumer trust and safety, the risk of fraud and counterfeit products, and the need to comply with regulations (De Vries et al., 2017). Studies have also noted that online marketplaces may face challenges managing conflicts between buyers and sellers, ensuring quality control, and maintaining a competitive advantage in a crowded market (Berman et al., 2018).

As another Fintech business model, lending platforms enable merchants to access capital quickly and easily. These platforms provide merchants access to a network of lenders willing to lend money to small businesses. Lending platforms are particularly useful for small merchants needing a credit history or collateral to obtain traditional bank loans.

Lending platforms often use technology to streamline the lending process, resulting in faster approval times and lower costs. Lending platforms have also contributed to the growth of peer-to-peer lending, enabling individuals to invest in loans and earn returns on their investments (De Roure et al., 2018). Several studies have identified various business models used by lending platforms, including marketplace lending, balance sheet lending, and hybrid models. Marketplace lending, where the platform matches borrowers with investors and takes a percentage of each transaction, is the most common (Lin, 2019). Studies have also explored the impact of platform design and features on borrower behavior, such as the use of credit scoring algorithms to assess borrower risk (Gao et al., 2020).

However, there are several challenges facing lending platforms, including the need to manage risk and ensure loan quality, the need to comply with regulations, and the risk of cyberattacks and data breaches (Li et al., 2018). Studies have also noted that lending platforms may face challenges in attracting and retaining investors, managing borrower default rates, and maintaining profitability (Grunert et al., 2020).

Finally, mobile wallets are used by merchants to improve their customer experience as a Fintech business model. Mobile wallets provide customers with a secure and convenient way to make payments. Customers can store their payment information in their wallets and use it to make payments online and in-store. Mobile wallets are handy for merchants who want to provide their customers with a seamless payment experience.

Choudhary & Choudhary (2020) systematically reviewed the literature on mobile wallet business models. The study found that the success of a mobile wallet business model depends on various factors, such as the adoption rate, pricing strategy, security features, and value-added services. In addition, Debnath & Bose (2021) reviewed the literature on business models of mobile payment systems, including mobile wallets. The study found that mobile payment systems can adopt various business models, such as transaction-based, subscription-based, and advertising-based models, depending on their target

market and revenue streams. Dua & Dhir (2020) examined the business models of mobile wallet firms in India, where mobile wallets have gained significant popularity. The study compared the business models of three major mobile wallet firms and found that they differ regarding their target market, revenue streams, and partnerships with other businesses. Rahman & Haque (2020) systematically reviewed the literature on business model innovation in mobile payment, including mobile wallets. The study found that mobile payment systems can innovate their business models by incorporating new technologies, creating new value propositions, and forging partnerships with other businesses.

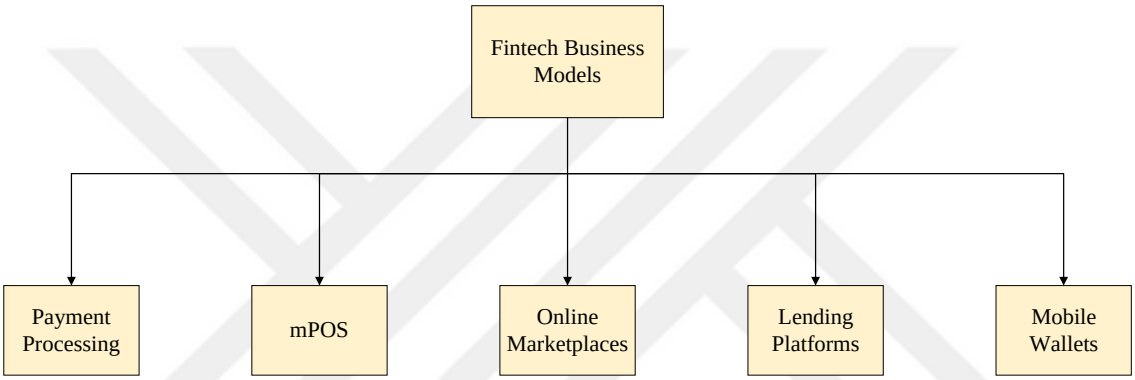


Figure 1.1 Fintech business models in the retail.

Furthermore, Fintech products are becoming increasingly popular among technology-driven customers in retail stores and online shopping. Mobile payments, virtual cards, P2P lending, mobile wallets, and robo-advisory are some of the most popular Fintech products that customers use today (Fig. 1.2). These products provide customers with a more convenient, secure, and efficient way to manage their financial transactions. As technology advances, we expect to see more innovative Fintech products that will continue transforming the financial services industry.

Mobile payments are one of the most popular Fintech products used by customers in retail stores and online shopping. Mobile payment technology allows customers to pay for goods and services using smartphones. This technology has revolutionized how customers make payments by offering a more convenient, secure, and efficient way to pay.

Research on mobile payments is expanding, encompassing studies on consumer adoption,

usage patterns, and its impact on the financial industry. For example, researchers found that trust, perceived ease of use, and perceived usefulness in mobile payments are critical parameters of consumer adoption (Laukkanen et al., 2021). Demirgüç-Kunt & Klapper (2012) found that mobile payments can increase financial inclusion by providing access to financial services for underserved populations. Virtual cards are another popular Fintech product that customers use in retail stores and online shopping. Virtual cards are digital representations of physical payment cards that customers can use to purchase online. Virtual cards are becoming increasingly popular because they provide customers with an extra layer of security and allow customers to keep their payment information confidential.

There has been considerable research on the use of virtual cards in the fintech industry. Gao et al. (2021) investigated the factors that affect consumers' adoption of virtual cards. The researchers found that perceived ease of use, usefulness, risk, and trust have impact on customers' decisions to use virtual cards. Mirza et al. (2020) explored the impact of virtual card adoption on customer satisfaction and loyalty. The authors found that customers who use virtual cards are more satisfied with their shopping experience and are more likely to remain loyal to the retailer. Moreover, virtual cards are a potential solution for reducing payment fraud and improving security in payment systems. Bhatia et al. (2019) examined the security features of virtual cards and found that they can offer more excellent protection against fraud than traditional payment cards.

P2P lending is a popular Fintech product that customers use to obtain loans for various purposes. P2P lending provides customers a fast, easy, and convenient way to obtain loans without collateral. P2P lending platforms facilitate the process by connecting borrowers with lenders and managing the transaction, often using sophisticated algorithms and credit scoring systems to assess borrowers' creditworthiness and determine the loan's interest rate and terms. P2P lending has emerged as a popular alternative to traditional bank lending, particularly for small businesses and individuals who may have difficulty obtaining credit through traditional channels. It offers borrowers access to affordable and flexible financing options while providing investors with higher returns than traditional savings accounts or low-risk investments.

Several studies have investigated the growth and impact of P2P lending and the factors

that influence borrower and lender behavior. A study by KPMG found that P2P lending has proliferated in recent years, with the global market expected to reach $1 trillion by 2025 (KPMG, 2019). Other studies have shown that P2P lending can help reduce the cost of credit for borrowers, improve financial inclusion, and promote economic growth (Agarwal et al., 2018; Burtch et al., 2018).

However, P2P lending also presents risks and challenges like credit risk, fraud, and regulatory uncertainty. Some studies have identified factors that can affect the performance and stability of P2P lending platforms, such as loan volume, diversification, and platform reputation (Gong et al., 2019; Yegen et al., 2019).

Mobile wallets, also known as digital wallets, are a type of mobile application that allows users to store and manage their payment and financial information on their smartphones or other mobile devices. Mobile wallets can be used to make payments, transfer money, and manage other financial transactions, such as tracking expenses and managing rewards programs. Mobile wallets have become an essential product of Fintech, providing customers with a convenient and secure way to make in-store and online payments. They also offer additional benefits such as loyalty rewards, cashback offers, and personalized offers based on user behavior.

A study by Deloitte found that mobile payments have become increasingly popular, with 27% of smartphone owners using mobile wallets to make payments (Deloitte, 2019). Another study by Juniper Research predicted that mobile wallets would process over $1 trillion in transactions by 2022 (Juniper Research, 2018). Hopalı et al. (2022) explained the mobile wallet popularity by years and its contribution to sustainability improvements.

However, mobile wallets also present some challenges and risks, such as security and privacy concerns and interoperability issues. Some studies have addressed factors affecting user adoption and trust, such as ease of use, trust in the provider, and perceived benefits (Lee et al., 2018; Liang et al., 2019). Overall, mobile wallets have become an essential and innovative product of Fintech, potentially transforming how people make payments and manage their finances. However, further research is needed to understand their full impact and potential and address the challenges and risks of this emerging market.

Robo-advisory is a relatively new technology in the world of finance that has gained

traction in the retail investment space. Robo-advisory is a digital platform that provides automated investment advice and management to retail investors using algorithms and software. The robo-advisor uses the investor's personal and financial information to recommend a portfolio of low-cost exchange-traded funds (ETFs) or mutual funds and monitors the portfolio continuously. Research on robo-advisory has explored various aspects of the technology, including its adoption by investors, its impact on the investment management industry, and its challenges. Studies have found that robo-advisory is gaining popularity among retail investors, particularly millennials, who are more comfortable with technology and digital platforms.

A study by PwC found that over half of millennials surveyed were open to using robo-advisory services. A study by Accenture found that 70% of millennials would consider using a robo-advisor for retirement planning (PwC, 2015; Accenture, 2016). Robo-advisory has disrupted investment management by offering a low-cost, convenient alternative to traditional investment advisors. A study by McKinsey & Company found that robo-advisory assets under management (AUM) are projected to reach $7 trillion by 2025, accounting for 10% of global AUM (McKinsey & Company, 2016). However, some studies have also found that robo-advisory may threaten traditional advisors, who may need help to compete with the low fees and convenience offered by robo-advisors (Korniotis & Kumar, 2018). On the other hand, several challenges facing the robo-advisory industry, including the need to build trust with investors, the potential for algorithmic bias, and the risk of cybersecurity breaches. Studies have also noted that robo-advisory services may not be appropriate for every investor, especially those with intricate financial circumstances or distinctive investment objectives (Kramm & Kräussl, 2018).

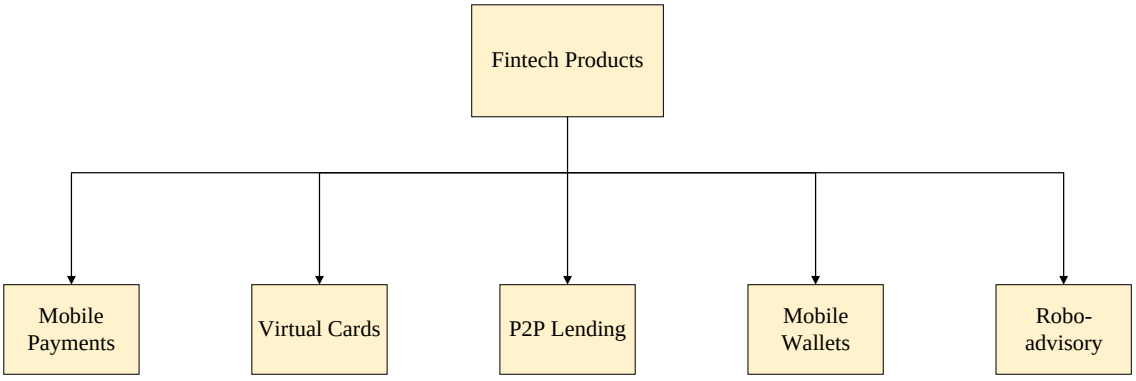


Figure 1.2 Fintech products in the retail.

2.2. Mobile Wallets

Customers demand fast, reliable, and more attractive payment methods in the new age where technology is developing rapidly, and its use is increasing in every field. Adopting an innovative, sustainable technology is inevitable to increase the competitive positioning and customer touch point in the market. Fintech services is a customer-centric product enabling merchants to provide fast, secure, ecologically traceable, innovative solutions. Incorporating Fintech services into payment services for physical stores and online retail platforms is a strategy that addresses the demand of technology-driven customers. Selecting and integrating suitable Fintech business models with the right timing and service design are essential for merchants (Gozman et al., 2018; Jiao et al., 2021). As payment methods and customer needs evolve, it is necessary to follow a correct and determined strategy to remain competitive. Smartphone shopping relies heavily on mobile wallets, which are a crucial aspect of Fintech services.

Although research and studies in this area are limited, the use of mobile wallets in stores and e-commerce has begun to increase with the development of technology and the expectations of technology-oriented customers. Smartphones have become a crucial banking channel due to the recent surge in wireless connectivity, internet network expansion, and easy accessibility. The rising usage of smartphones has significantly contributed to increasing demand for mobile wallet services among both social customers and merchants, thanks to the advent of M-banking (Shaikh & Karjaluoto, 2015; Dauda & Lee, 2015). This Fintech component securely stocks tokens, payment information, loyalty card information, and digital coupon information, allowing customers to shop securely in-store and via e-commerce. Mobile wallets integrate with payment service providers, financial institutions, banks, merchants, retailers, telecom operators, and many other businesses to provide improved and valuable customer services (Amoroso & Watanabe, 2012).

Wadhera et al. (2017) described four types of mobile wallet structures. Open wallets are linked to a bank and make it possible to offer a reloadable (e.g., M-Pesa) cash withdrawal service at the retail or agency exit. Airtel Money and other semi-open wallets connect with a bank but do not permit cash withdrawals. On the other hand, Paytm and other semi-closed wallets enable shoppers to purchase products from vendors integrated with the

service provider. While semi-closed wallets would not receive refunds, they could be reloaded. Closed wallets, like Gift Vouchers, do not permit customers to withdraw cash, nor can they be converted into cash by reloading them. A digital wallet that employs various advanced technologies is known as a mobile wallet. This service may use barcodes, and Quick Response (QR) codes as enabling technologies. QR technology, which is fast and secure, can serve as authentication for monetary transactions in a mobile wallet.

Unmanned retail stores like Bingo Box and Amazon's Go provide technologically advanced customers with innovative processes through automated services, such as mobile payments and business models integrated with cutting-edge technology. To enter these stores, consumers scan QR codes with their smartphones. At the end of the purchasing process, consumers complete their shopping using the mobile wallet service (Wu et al., 2019). In addition, mobile wallets may contain NFC, another secure and fast technology. Customers can benefit from contactless payment services thanks to the NFC payment system. Customers use NFC technology to purchase by holding their smartphones to a reader in-store or shipping services (Dauda & Lee, 2015). Another example of using NFC is the Walmart NFC Payment System to transfer money from one device's screen to another over short distances (Leong et al., 2020).

NFC technology accelerates and streamlines the payment procedure for shoppers who can finalize their in-store smartphone purchases. By converting the payment procedure into a frequency wave, NFC enables a seamless transaction experience. The adoption of integrated mobile wallets with NFC technology has been led by features such as testability, sustainability, compatibility, perceived usefulness, perceived risk, the attractiveness of alternatives, absorptive capacity, and innovativeness (Pham & Ho, 2015). While mobile wallet technology offers improved solutions for payment service providers, merchants, retailers, and financial institutions, it offers innovative, sustainable, fast, and secure services compared to traditional payment methods (Dauda & Lee, 2015). Retailers are looking for ways to increase customer retention by taking advantage of the benefits of mobile technology. One of the products they rely on for this is digital loyalty programs. Mobile wallet-integrated loyalty card programs offer convenience for both in-store and online shopping. According to Caro & Sadr (2019), smart card-based loyalty programs can be quickly scanned via the phone screen at the point of sale (POS) or in

close proximity to the store entrance, leading to an improved user experience and increased trustworthiness. In this way, customers can avoid physically carrying loyalty cards. Moreover, by integrating mobile wallet services, customers can benefit from sustainability and ease of use (Kumar et al., 2017).

Enabling mobile payments on the web involves several complex factors that require compliance, including ensuring a secure payment mechanism, incorporating multiple electronic payments, and facilitating receipt transactions and shopping. Mobile wallets like Apple Pay (Ruiz-Martinez, 2015) continuously evolve to ensure the security and interoperability of essential processes. This pioneering approach assures customers of a reliable and seamless payment experience. Chopdar et al. (2018) employed the Unified Theory of Acceptance and Technology Use 2 (UTAUT2) to investigate customer adoption of mobile payment applications. The study revealed that privacy concerns and security risks impact customer behavior. In addition to network expansion and smartphone penetration, improvements in mobile payment infrastructure are constantly improving the customer experience. In particular, the omnichannel integration structure, eco-friendly features, and user-friendly features allow mobile wallets to provide a shopping experience preferred by customers (Chopdar & Balakrishnan, 2020). In addition, IoT technology uses data from customers' smartphones. Customers carry their smartphones with them constantly, so IoT allows them to be tracked during store visits. Developments in this area especially enable the retailer to learn about customer preferences (Caro & Sadr, 2019).

Thanks to their subscribed customers, platform-based mobile payment service providers with strong IT expertise have good mobile market knowledge. Examples of these are Facebook and Alibaba. On the other hand, mobile payment providers need more market experience and consumer trust than they currently have. To attain this objective, it is crucial to possess both proficiency in information technology and the ability to integrate it effectively. Mobility, price, perceived risk, trust, information security, quality, network externality, social impact, observability, technical concerns, compatibility, testability, and self-expression are essential for integrating mobile wallets with e-commerce and retail stores (Lee et al., 2019). One of the most remarkable opportunities of mobile payment services is minimizing the risks and revealing the maximum benefit for merchants. Mobile payment services such as Google Wallet, Apple Pay, and Samsung Pay improve

the customer experience and reduce customer churn by providing enhanced security services online and offline. They ask their users to complete complex authentication steps to increase security and raise awareness about protecting customer privacy (Park et al., 2019).

Mobile wallet technology has developed rapidly in the last decade, attracting customers' and companies' attention. However, mobile wallets are a very new technology in development, and new features can be added according to customer and merchant requirements. As a way to support this situation, it is seen that there were only sporadic studies in the literature before the studies started to increase after 2015. As a new field with limited research, studies focusing on mobile wallets have gradually increased since 2015. Understanding the ever-evolving services of mobile wallets is very important as it follows the development areas of a developing technology-oriented product and directs future studies. Academic studies frequently regarded mobile wallets as a component of mobile payment trends or a fresh addition to the Fintech ecosystem without conducting a thorough literature review on the topic. When the literature review studies related to this subject are examined, the subject has started to be studied quite recently. In their literature review on the evolution of the finance sector over the past few decades, Turkmen & Degerli (2015) categorized mobile wallets as an element of pioneering banking trends. Dennehy & Sammon (2015) and Karsen et al. (2019) performed comprehensive literature reviews on mobile payments, where mobile wallets were recognized as innovative advancements. Ramli & Hamzah (2021) conducted the first literature review focusing on mobile wallets, at least in part. Nonetheless, the research solely scrutinized mobile wallets in emerging markets and, from the technology adoption perspective, could not bring a holistic perspective. The most comprehensive study in this field has been made by Hopalı et al. (2022) via scanning the literature for the last ten years of mobile wallets, evaluating mobile wallets from a sustainability perspective, and suggesting future research.

This study holds significant value for both managers and scholars since there is a pressing need for an extensive survey of mobile wallet literature. One of the primary aims of this thesis is to bridge the research gap by scrutinizing articles published from 2012 to 2022 in reputable databases such as Science Direct, Scopus, and Web of Science. The literature encompasses a wide range of subjects, including the technology adoption for mobile wallets, customer engagement, competitiveness, and security and privacy concerns. This

thesis has classified and provided detailed information on these topics. Additionally, it has proposed novel recommendations to improve research direction and promote a deeper comprehension of mobile wallet services through a systematic literature review.

2.2.1. Survey Analysis and Statistics

The methodology adopted in this study for the literature review involves examining the current usage of mobile wallet technology. The survey approach is depicted in Figure 2.1, which begins with the identification of scientific databases containing relevant articles on the research topic. Through the thesis, a literature survey is conducted by searching via Science Direct, Scopus, and Web of Science databases. To filter the publications, a set of specific policies and criteria is applied, including the requirement for the article to be in English, have the full text available, published in a peer-reviewed academic journal, and have a publication date falling between 2012 and 2022. The scope of the search is restricted to the "topic," comprising the article's title, abstract, and keywords. The chosen keywords were not exclusively related to mobile wallets. The findings indicate that electronic and digital wallets rely on mobile devices and are referred to by the same technology in the literature (Kaur et al., 2020; Bezovski, 2016; Leon, 2021; Junaid, 2015). Therefore, the search was conducted using the keywords: "mobile wallet," "e-wallet" and "digital wallet."

Firstly, an initial abstract reading and skimming phase was completed, and it was found that 232 articles satisfied the predetermined inclusion criteria. Then, these articles underwent further analysis through complete reading. Out of the 232 articles, it was identified 128 publications as research hotspots in the domain of mobile wallets across the Science Direct, Scopus, and Web of Science databases. By categorizing the articles based on their publication year, published database, and research topics, this thesis could better organize the filtered publications and gain a deeper understanding of the present research trends in mobile wallets.

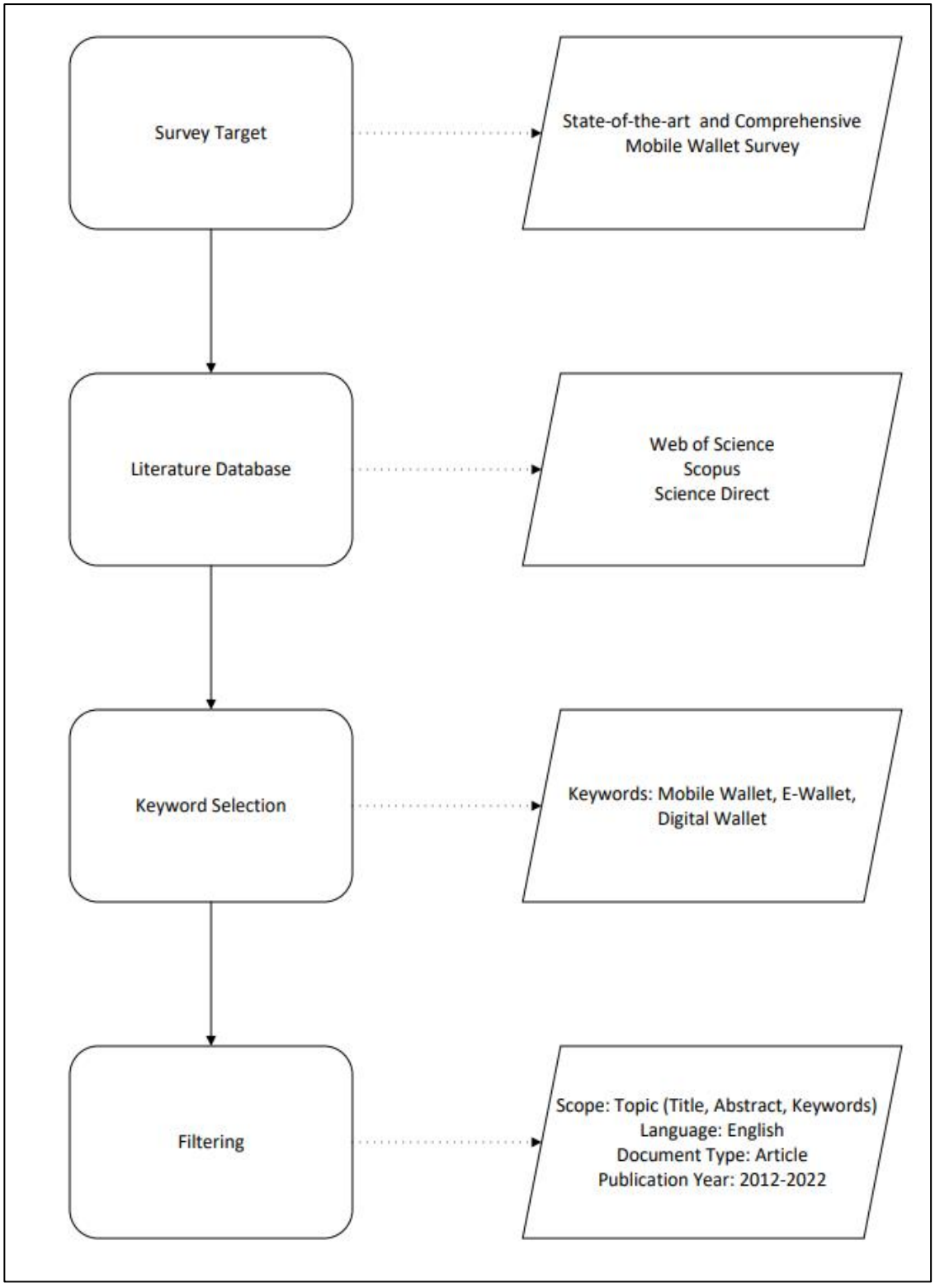


Figure 2.1 Survey method.

2.2.1.1. Years of Publication

The publications selected for analysis in this study were limited to the period between 2012 and 2022, as the mobile wallet is a relatively new research field that has gained momentum in the last decade. The "mobile wallet" term was not widely employed initially. However, with the advancement of Fintech and the growing number of technology-oriented consumers, the utilization and research related to this field have increased. This trend is evident in the significant increase in publications in recent years, reflecting the growing adoption of mobile wallets in stores and online channels. Figure 2.2 depicts the attention that this new research phenomenon has garnered since 2018.

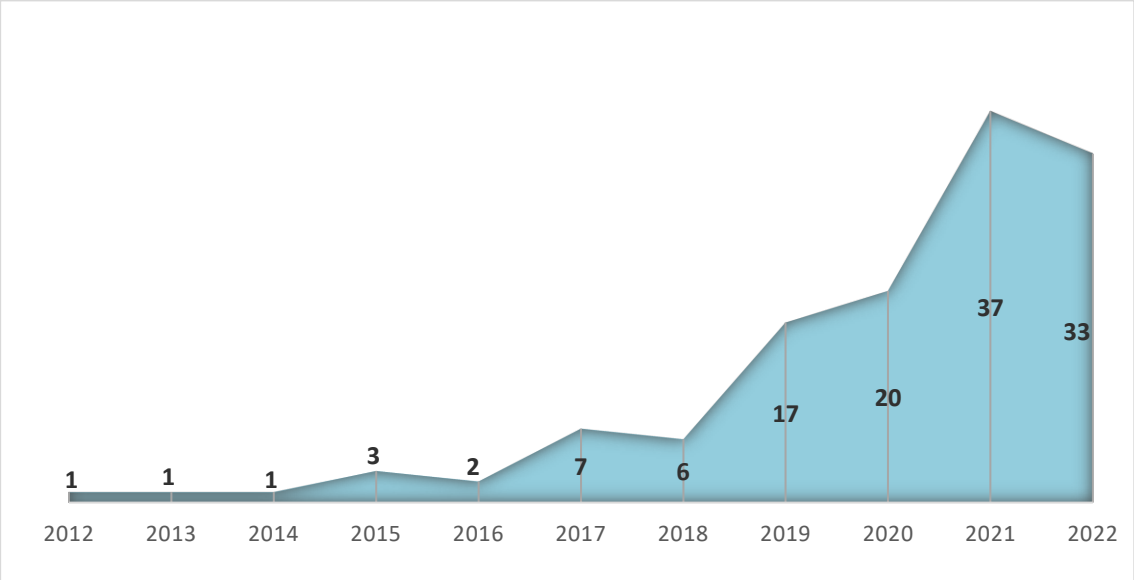


Figure 2.2 Publication by years.

2.2.1.2. Academic Research Databases

In order to provide a comprehensive survey, this study systematically examined several reputable academic research databases such as Science Direct, Scopus, and Web of Science. The selection of various databases aimed to cover a broad spectrum of research and facilitate a deeper comprehension of mobile wallets' academic impact and direction. Fig. 2.3 illustrates the distribution of articles across these databases. Scopus contained the highest number of articles, with 97, while the lowest number was found in Science Direct, with only 22 articles. Web of Science had 58 articles published between 2012 and 2022. Moreover, nine articles were found to be published in all three databases.

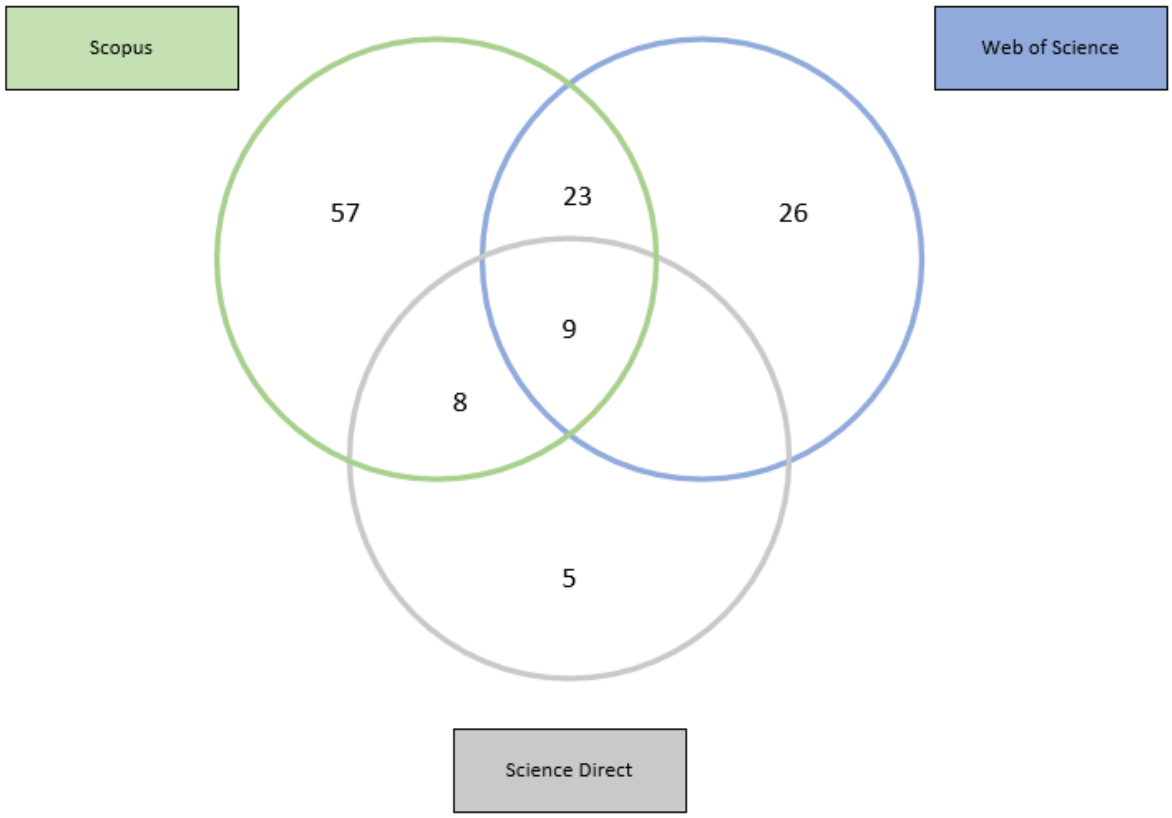


Figure 2.3 The mapping of the academic research database about mobile wallets.

2.2.1.3. Research Topic

To better understand mobile wallet usage and analyze the scope of research in this field, research topics have been classified into four groups. The research topics pertaining to the period from 2012 to 2022 have been depicted in Fig. 2.4 Among the various research topics, the Technology Adoption of mobile wallets has emerged as the most prominent area of investigation in the existing literature. This area involves exploring the factors that influence customers' adoption of mobile wallets and how they increase their usage. This research domain includes factors determining the inclination to use, customer attitudes, and mobile wallets' pre-and post-acceptance operational characteristics. The second most investigated category is customer engagement, with 21 papers focusing on consumer loyalty, satisfaction, and campaign management regarding mobile wallets. Immediately after customer engagement, the most investigated research area is competitiveness, with 14 articles comprising sustainability, innovation, and service quality-related research.

Security and Privacy are the final research areas with a similar research interest.

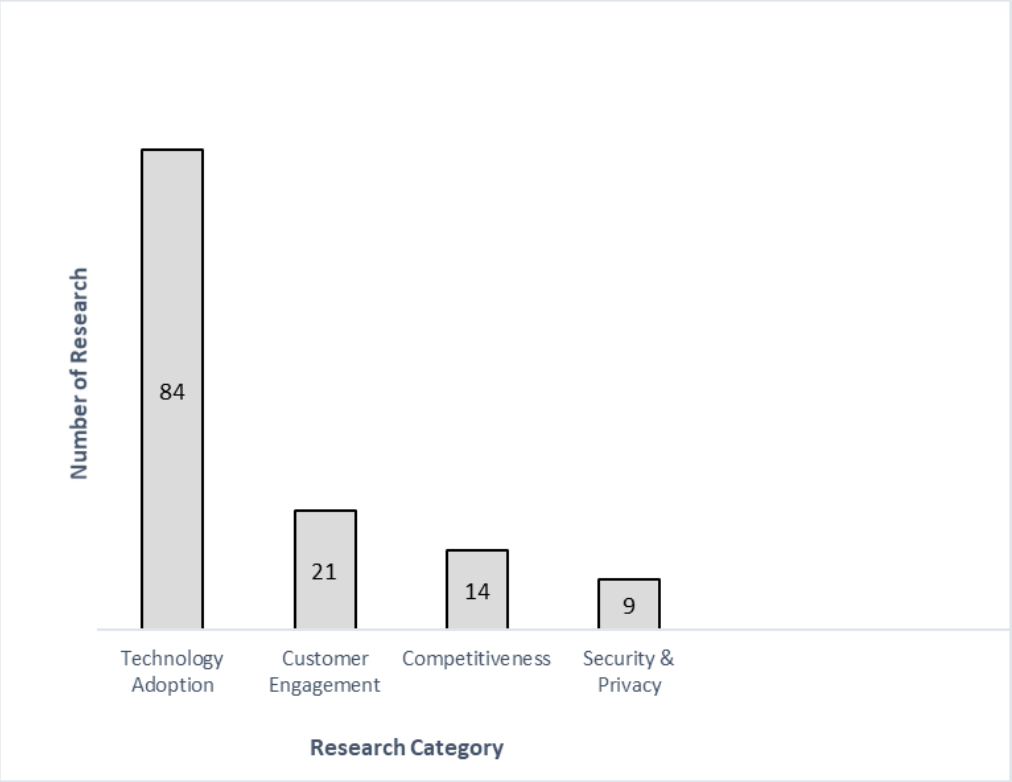


Figure 2.4 Research topics.

2.2.2. A Comprehensive Literature Review of Mobile Wallets

The study conducted a comprehensive review of literature across three databases, which revealed that mobile wallet research is broadly categorized into four key areas: adoption of technology, engagement of customers, competitiveness, and security and privacy. In the continuation of this section, these issues are analyzed and presented in detail in the literature.

2.2.2.1. Technology Adoption

By providing a smartphone application, a service provider offers a digital service known as a mobile wallet that empowers users to conduct electronic transactions, transfer funds, make donations, utilize digital coupons and loyalty cards at physical stores, and shop online (Sharma et al., 2018; Slade et al., 2015). Given that this technology emerged approximately a decade ago, several researchers have focused on comprehending customer-centric adoption criteria. Examining the touchpoints of mobile wallet research is essential for comprehending the future trajectory of this technology.

How consumers choose to pay for their purchases can have a notable effect on both the frequency and quality of the products they buy. Prior studies have identified factors associated with the adoption of various payment methods. For example, in their study, the adoption of mobile wallets was analyzed by Malik & Sharma (2021) through the use of weight analysis, which helped identify significant and non-significant constructs. On the other hand, Vasantha & Sarika (2019) focused on demographic variables, like personal innovativeness and age, that can affect the inclination of mobile wallet usage. Shekhar & Jaidev (2022) discovered that perceived enjoyment and personal innovativeness have a positive relationship with perceived ease of use in the context of mobile wallets. Ariguzo & White (2013) conducted a study on M-PESA adoption in Kenya, examining distinctions between individuals who have adopted mobile wallets and those who have not. Dauda & Lee (2015) utilized conjoint analysis to examine consumer preferences for forthcoming online banking services. The findings suggested that Nigerian banks could improve their competitive advantage by enhancing mobile wallets' perceived ease of use and entertainment features.

In their research, Abbasi et al. (2022) employed Fuzzy Set Qualitative Comparative Analysis (fsQCA) and Structural Equation Modeling (SEM) to investigate the factors that affect customers' intention to continue using mobile wallets. Their findings demonstrated that the most critical factor is service quality, as symmetrical outputs indicate. However, asymmetrical outcomes suggest that a combination of system quality, service quality, perceived usefulness confirmation, perceived ease of use confirmation, security confirmation and information quality is necessary. Factors related to the system and the user were discovered to be significant drivers of adopting Near Field Communication (NFC) mobile wallets (Hor et al., 2021). Pham & Ho (2015) explored mobile wallets in the context of NFC-based payment services and determined that perceived usefulness and compatibility were the primary catalysts for adoption.

Shaw et al. (2022) conducted a multinational study on the adoption of mobile wallets in Germany, Canada, and the United States. The researchers employed a conceptual Diffusion of Innovations (DoI) model to examine the acceptance process. Additionally, the model was augmented concerning the context-relevant constructs, like ubiquity, security, and privacy. The outputs provided support for the proposed model; however, it was discovered that the levels of security risks, privacy concerns, and ubiquity varied

across countries. Mobile wallet service providers must ensure that their privacy and security policies align with user perceptions (Soodan & Rana, 2020). Moreover, the reputation of service providers was found to be a crucial determinant of continuance intention, perceived security, and trust, as noted by Garrouch (2021). To attract more consumers, Nguyen & Nguyen (2022) recommended that payment service providers prioritize the convenience, safety of mobile wallet services, perceived usefulness, and perceived ease of use.

Phuong et al. (2020) identified several key factors that influence customers' intention to use mobile wallets in Vietnam. These factors include mobile application quality, situational normality, feedback mechanism, mobile wallet familiarity, and payment security. Their analysis revealed that feedback mechanisms and payment security positively impact satisfaction, trust, and willingness of mobile wallet usage. Moreover, mobile wallet familiarity and application quality affect perceived ease of use, perceived usefulness, and mobile wallets' inclination usage. In their research, Talwar et al. (2020) examined data from first-time users of mobile wallets to evaluate a two-step model encompassing both pre-adoption and post-adoption elements. According to the findings, initial trust is positively impacted by service quality and information, whereas perceived usefulness and continuance intention are positively associated.

Likewise, Gupta et al. (2020) investigated the significance of post-adoption satisfaction and continuance intention in the context of an extended expectation-confirmation model. Their results demonstrated that pre-adoption performance expectations played a crucial role in consumption-driven confirmation, which subsequently influenced satisfaction, perceived usefulness, and perceived security. In a separate study conducted in Jordan, the issue of post adoption was also examined by Obidat et al. (2022). Their findings indicated that perceived ease of use and perceived usefulness were more influential than subjective norm in motivating customers to sustain the usage of mobile wallets.

Leong et al. (2020) utilized an ANN model to predict resistance to mobile wallet adoption and demonstrated that income, education, usage, perceived novelty, value, tradition, and risk significantly influenced adoption. Meanwhile, Kaur et al. (2020) utilized the DoI theory to emphasize the importance of comprehending customers' intention to use mobile wallets. Their cross-sectional survey of smartphone users showed that compatibility,

relative advantage, observability, and complexity were highly associated with intention to use, while trialability had no effect. Menon & Ramakrishnan (2019) identified challenges and inclinations associated with wallet adoption, while the impact of smartphone addiction on adoption was investigated by Shaw & Kesharwani (2019) investigated as a moderating factor. The study discovered that subjective norms, perceived usefulness, and perceived ease of use were crucial factors in assessing the intention to use mobile wallets. A study by Amoroso et al. (2021) among smartphone owners in the Philippines resulted in the development of a model that integrates trust, loyalty, switching costs, habit, reciprocity, and future repurchase. They found that habit was the most significant mediator, and while switching costs were not high, they still played a role in adoption. Mobile wallets have become a crucial component of payment processing as the world moves toward a cashless economy. The utilization of smartphones and the accessibility of internet services, both in urban and rural areas, are rapidly increasing.

In India, the two most crucial factors that influence merchant intention to adopt mobile wallets are the perceived usefulness and customer value addition, as determined by Singh & Sinha (2020). Gupta et al. (2022) developed a comprehensive model utilizing the TTF and UTAUT models and analyzed the elements that affect merchant intention to adopt mobile wallets, with price value and perceived trust being the main factors. According to the research, the most critical factor affecting the inclination to adopt mobile wallets is the fit between the technology and the tasks involved. In Canada, Shaw (2014) conducted a study investigating the acceptance of mobile wallets. The findings revealed that retailers are likely to invest in upgrading their store equipment to adopt this technology only after the customers' widespread acceptance is demonstrated. The Technology Acceptance Model (TAM) was utilized in a proposed model that incorporated contextual factors such as trust and informal learning to explore mobile wallet acceptance. The study found that perceived usefulness was the most significant factor in influencing mobile wallet acceptance, while trust mediated the effect of informal learning. Tripathi et al. (2022) introduced a model tailored to small physical retailers that consider subjective norms and attitudes that promote perceived usefulness and mobile wallets' intention to use. The study revealed that the decision to use mobile wallets is positively influenced by trust, while the perceived cost negatively impacts the usage intention.

According to Shah et al. (2017), security concerns continue to limit mobile wallet adoption by new customers despite being aware of this payment method. Gupta's (2022) research highlights that the perceived risk associated with mobile wallets negatively affects customers' views on the usefulness of the technology, their motivations for using it, and its overall purpose. In another study, Mombeuil & Uhde (2021) explored the continuous intention of foreign customers residing in China to use mobile wallet technology. They examined WeChat Pay users and analyzed the impact of mobile wallet advantages, relative convenience, privacy, and security on the mobile wallets' inclination to use. The study revealed that each independent variable positively affected the intention to use mobile wallets.

WeChat Pay provides enhanced security, privacy protection, and greater convenience and benefits than traditional payment methods. Mombeuil (2020) investigated the impact of relative convenience, perceived security, perceived privacy, and relative advantage on Chinese users' updated inclination to adopt mobile wallets. The research indicated that perceived security and comparative advantage were the most robust predictors of continued adoption. On the other hand, Sharma et al. (2018) proposed a hierarchical framework while investigating the intricate relationship between mobile wallet acceptance inhibitors in Oman. The study identified new technology discomfort, the complexity of innovative product development, lack of awareness about the benefits of portable wallets, and lack of skills in using new technology as the primary inhibitors to the inclination of mobile wallet usage.

Chawla & Joshi (2019) developed a mixed research model. According to the study's findings, mobile wallet usage among Indian users can be explained by critical factors like facilitating conditions, perceived ease of use, perceived usefulness, lifestyle compatibility, security, and trust. Talwar et al. (2021) examined how positive and negative word of mouth (PWOM and NWOM) affected the inclination of mobile wallet usage in their study. The results indicated that perceived ability, perceived information quality, and perceived benefit were significant determinants of PWOM, while perceived cost, perceived uncertainty, and perceived risk were important NWOM parameters. Although, the study uncovered that only PWOM significantly impacts the continued mobile wallet usage intention.

The factors that drive perceived satisfaction, customer intention, and mobile wallet usage recommendations in India were investigated by Singh et al. (2020). According to the study, attitude, perceived risk, perceived ease of use, and perceived usefulness were found to be the most influential factors in determining recommendation to use, perceived satisfaction, and inclination toward mobile wallet usage. The impact of critical mass, self-efficacy, and flow theories on mobile wallet adoption in the hospitality industry was studied by Lew et al. (2020). The researchers discovered that perceived enjoyment, perceived critical mass, perceived usefulness, perceived ease of use, and perceived self-efficacy were the primary inhibitors that significantly influenced mobile wallet adoption. Using a daily bilateral user transfer dataset, Leon (2021) investigated the network of Colombian mobile wallets. The study's results suggested that mobile wallets are frequently used for person-to-person, person-to-business, and business-to-business transfers in Colombia, which highlights the increasing mobile wallet acceptance among customers and the complexity in the Colombian market. The study by Campbell & Singh (2017) investigated user innovativeness in digital payment acceptance and behavioral inclination of mobile wallet usage in India. According to the research, perceived ease of use was crucial in determining the behavioral mobile wallets' intention to use. However, unexpectedly, innovativeness and perceived usefulness did not have a positive impact on the intention to use mobile wallets.

Madan & Yadav (2016) conducted a study on the impact of promotional benefits and perceived regulatory support on the adoption of mobile wallets. Their findings showed that factors such as facilitating conditions, social influence, performance expectancy, perceived value, perceived risk, as well as promotional benefits and perceived regulatory support, significantly influence the inclination to use a mobile wallet.

In a study conducted in Thailand, Amoroso & Ackaradejruangsri (2017) examined customer attitudes toward mobile wallet applications by studying their repurchasing intentions, loyalty, and satisfaction. The researchers discovered a strong correlation between customer attitudes and perceived usefulness, perceived ease of use, and personal innovativeness. In another study, the findings of Senali et al. (2022) indicated that the relationship between perceived compatibility and inclination to adopt mobile wallet technology is negatively moderated by personal innovativeness. The study conducted by Adjei et al. (2020) confirmed that the level of customer satisfaction significantly

influences the continued mobile wallet usage and financial services. Meanwhile, the study conducted by Chaddha et al. (2021) examined the effect of celebrity endorsers' reputations on the inclination to purchase through mobile wallets in India. According to the results, the reputation factors of the TEARS model have a positive impact on shopping intentions through mobile wallets. Vidushi & Kashyap (2021) proposed a model that illustrates how the use of click-and-collect technology, smartphones, mobile wallets, and digital signage in physical stores can influence changes in purchase intention for a range of technology products that provide an online customer experience.

Phutela & Altekar (2017) utilized the UTAUT model to evaluate trust in service providers and mobile wallet users. Similarly, Estiyanti et al. (2021) examined the mobile wallets' inclination to use in Indonesia by merging TAM with perceived usability. Their findings suggest that perceived usefulness, usability, and enjoyment are significant factors that positively affect mobile wallet adoption. Furthermore, To & Trinh (2021) used an extended TAM to identify the primary factors that explain the intention to use mobile wallets in Vietnam. Their research indicates that perceived usefulness, perceived ease of use, and perceived enjoyment have a positive influence on the inclination to use mobile wallets.

In their research, George & Sunny (2021) explained technology adoption models and behavioral studies regarding mobile wallets. They aimed to understand the factors that influence continued usage of mobile wallets, leading to the development of a thorough conceptual framework for the adoption of mobile wallets. In an effort to comprehend the essential elements driving mobile wallet adoption in Singapore, Seetharaman et al. (2017) developed an extended TAM model. Their model encompassed factors such as transaction speed, transaction cost, flexibility critical mass, trust, transaction security, availability of alternatives, consumer privacy, innovativeness, and anonymity. Singh et al. (2017) found that perception, usage, satisfaction, and preference are significantly associated with mobile wallet adoption, whereas security, trust, and hedonism play a lesser role. They proposed an integrated UTAUT model aimed at comprehending the inclination to use mobile wallets.

Furthermore, Chauhan et al. (2022) pointed out Indian banks' apprehension that Fintech-related services, like mobile payment, e-banking, and mobile wallet, are not broadly

embraced by the public. To tackle this, they expanded the UTAUT2 model and clarified consumer intention to use several e-banking services by incorporating factors such as security, information availability, perceived risk, and consumer innovativeness.

Alaeddin et al. (2018) investigated the attitude and intention of consumers to switch from a traditional wallet to a digital wallet. According to their findings, the consumer's attitude towards switching was significantly influenced by the perceived usefulness and perceived ease of use. Ansari et al. (2021) suggested that the millennial generation's constant interaction with technology and increasing internet connectivity led to digital wallet adoption. Using the extended TAM, Soe (2022) demonstrated that stable internet connections positively impacted the perceived usefulness of mobile wallet owners. The study also suggested that governments could play a role in ensuring stable internet connections in this regard. To understand mobile wallet adoption, Singh & Ghatak (2021) extended the TAM model to include ease of use, usefulness, risk, compatibility, cost, behavioral intention, and actual usage. Persada et al. (2021) employed the Theory of Planned Behavior (TPB) framework to assess Generation Z's behavioral inclination toward utilizing mobile wallets for online transactions and in-store. By incorporating technology anxiety, perceived value, and perceived credibility factors, Thanigan et al. (2021) expanded the UTAUT model. After comparing the new model to the original, the researchers concluded that the former demonstrated more substantial explanatory power and greater robustness.

Bommer et al. (2022) conducted a meta-analysis to investigate the correlation between the adoption of mobile wallets and the factors that lead to adoption using an extended UTAUT model. The results indicated that facilitating conditions, hedonic motivation, social influence, and price value positively impacted users' inclination to use mobile wallets.

Similarly, Bailey et al. (2022) focused on a bank-sponsored mobile wallet and examined its adoption among Latin American customers. They used a revised UTAUT2 model, which included variables such as facilitating conditions, consumer innovativeness, effort expectancy, performance expectancy, consumer insecurity, consumer optimism, bank trust, and perceived quality. Sobti (2019) proposed an extended version of the UTAUT model. This model incorporated the demonetization effect, perceived risk, and perceived

cost to comprehensively examine the factors influencing the behavioral inclination toward using mobile banking and mobile wallet usage in India. The findings of their study indicated the significant impact of demonetization and facilitating conditions on the adoption of technology.

Chawla & Joshi (2021) proposed a research methodology by integrating the TAM and UTAUT models. Their recommendation for mobile wallet service providers was to prioritize lifestyle compatibility, perceived usefulness, and security in order to enhance the adoption of mobile wallet services. Wamba et al. (2021) combined social collectivism, human orientation, external factors, and an extended version of the TAM model to examine the factors that influence the inclination to use mobile wallets in Cameroon. In their research, Sukwadi et al. (2022) utilized an extended TAM to comprehend the adoption of mobile wallets in Indonesia. Their study revealed that mobility, perceived ease of use, and social influence are significant factors that contribute to the intention to use mobile wallets. Amoroso & Magnier-Watanabe (2012) introduced a comprehensive model that accounts for consumer-related variables in elucidating the swift proliferation of mobile wallets in Japan. Limantara et al. (2021) used a proposed UTAUT model to confirm that perceived risk, performance expectancy, and social influence are crucial factors for the inclination of mobile wallet usage in Indonesia.

In a study by Lee et al. (2022), the focus was on determining the level of satisfaction and enjoyment that Generation Y and Z in Malaysia experienced when using mobile wallets. The study found that the positive effect of perceived enjoyment on impulse buying was evident among these age groups, whereas satisfaction did not have a direct impact. The study conducted by Sarmah et al. (2021) examined millennials' inclination toward adopting mobile wallets. They demonstrated that perceived ease of use and perceived usefulness contribute to usage inclination, while trust plays an important role in actual usage. Kumar et al. (2018) presented a study concerning young Indian users' inclination toward adopting mobile wallets, revealing that adoption and satisfaction were significantly influenced by security, perceived ease of use, and perceived usefulness. Taheam et al. (2016) studied the determinants of mobile wallet adoption among young individuals in India. They highlighted the importance of considering factors like social influence, controllability, security, performance enhancement, and perceived usefulness in the design of mobile wallets.

Remarkable popularity in mobile wallet utilization was observed throughout the pandemic. Several studies have indicated that factors such as lifestyle compatibility, facilitating conditions, perceived usefulness, perceived ease of use, trust, perceived risk, the convenience of application, effort expectancy, price-saving orientation, skillfulness, social influence, government support, and the COVID-19 pandemic anxiety play a role in influencing customer behavior and intention to use mobile wallets. For instance, research conducted by Alswaigh & Aloud (2021) and Ming & Jais (2022) found that perceived usefulness, social influence, and government support are positively associated with the attitude toward using mobile wallets throughout the pandemic. Additionally, Astari et al. (2022) revealed that the fear of the pandemic could heighten the inclination toward using mobile wallets. Furthermore, trust and effort expectancy were identified as crucial factors by Ly et al. (2022) in shaping the inclination to use mobile wallets, while Al-Qudah et al. (2022) emphasized the significance of skilfulness and convenience of application during the COVID-19 pandemic. To sum up, these studies provided valuable insights into the factors contributing to the adoption and use of mobile wallets during the pandemic.

Recent research has shed light on the factors influencing the adoption and use of mobile wallets. Ojo et al. (2022) found that facilitating conditions, perceived government support, and perceived COVID-19 risk are important in influencing the inclination to use mobile wallets. Similarly, in a study by Jaiswal et al. (2022), the key antecedents of intention to use were identified as facilitating conditions, performance expectancy, effort expectancy, and individual mobility. Meanwhile, Thaker et al. (2022) stated that social influence, performance expectancy, trust, facilitating conditions, hedonic motivation, and habit were the drivers of mobile wallet usage among Malaysian customers. In their study focused on Malaysia, Lui et al. (2021) aimed to enhance mobile wallet adoption. Their findings revealed that perceived usefulness and compatibility were significant factors influencing the inclination to use mobile wallets.

Tran & Hien (2021) discovered that the mobile wallets' perceived value positively affects customer commitment and recommendation. On the other hand, Reddy & Rao (2021) classified mobile wallet users into different customer clusters to better understand the actual usage. These findings demonstrate the intricacy of the factors that influence the adoption and usage of mobile wallets, providing valuable insights for practitioners and researchers in this domain.

Several studies have investigated the factors influencing mobile wallet adoption. Fanuel & Fajar (2021) proposed a model that combines TAM with both technological features and social surroundings to pinpoint the key factors driving mobile wallets' adoption, including perceived security, job relevance, personal experience, and subjective norms. In their study, Chawla & Joshi (2020) investigated the influence of age and gender on the factors that drive mobile wallet adoption, revealing that male and young customers are more inclined to adopt this technology. Similarly, the study of Reddy & Rao (2019) in Spain discovered that personal innovativeness holds more significant sway over women's mobile wallet adoption, while the social environment influences men. Sharma et al. (2019) conducted research in India. They identified perceived ease of use, mobility, usage cost, convenience, trust, privacy, flexibility, transaction speed, and anonymity as factors affecting customer inclination to use mobile wallets. Meanwhile, Malik et al. (2019) determined that performance expectancy, trust, and incentives positively affect the adoption of mobile wallets. However, they discovered that perceived ease of use, perceived enjoyment, aesthetics, and social influence did not directly affect adoption. Kavitha & Kannan (2020) used an expanded TAM to determine that perceived usefulness, ease of use, and risk are critical factors that impact the adoption of mobile wallets. These studies have offered valuable insights into the drivers of mobile wallet adoption and can guide the creation of effective strategies to promote their use.

2.2.2.2. Customer Engagement

Customer engagement is crucial for the success of mobile wallets as it plays a pivotal role in building customer loyalty and increasing adoption rates. Customer engagement drives customer adoption, retention, and advocacy for mobile wallet services. By engaging with customers, mobile wallet providers can create personalized experiences catering to individual needs and preferences, enhancing customer satisfaction. Through effective engagement strategies, mobile wallet providers can also gather valuable insights about customer behavior and preferences, which can be used to improve service offerings and drive innovation. Moreover, customer engagement helps to build trust and credibility with customers, which is critical in a highly competitive market.

Customer engagement extends beyond a simple transaction and involves a continuous relationship between the shopper and the company. For emerging services like mobile

wallets, it is essential to implement effective strategies that foster customer engagement and establish a competitive position. Kumar et al. (2019) proposed a research model that examined the integration of mobile wallets with customer engagement and discovered an S-shaped relationship between the two. Shankar & Behl (2021) used a mixed-method approach focused on data to investigate the mobile wallet customer experience, while Ocak & Cagiltay (2017) employed a cognitive model and end-user usability testing to evaluate the mobile wallet app's touch screen. The outcomes revealed that interactivity, convenience, security, privacy, and contact are the principal drivers of customer experience.

Customer engagement heavily relies on customer loyalty, which determines the decisions to keep using brands of mobile wallets. In their study, Gong et al. (2020) conducted a research on the brand equity and customer loyalty of AliPay Wallet and WeChat Wallet, finding that service-strategy complementarities, platform application, and application service have a positive impact on both customer loyalty and brand equity. In their study on the pattern use of mobile wallets in India, Manickam et al. (2022) discovered that despite encountering obstacles such as network issues, transaction failures, and monetary losses, customers exhibit loyalty towards certain brands such as PayTm and Google Pay. The study by Matemba et al. (2018) centered on the determinants of customer loyalty concerning WeChat wallets. They discovered that convenience, perceived availability of merchant support, and social influence play a significant role.

Furthermore, Chohan et al. (2022) explored consumer loyalty toward QR code use in mobile wallets. Their study highlights the significance of trust, customer satisfaction, and a solid commitment to using QR codes for payments as crucial factors in fostering customer loyalty. To enhance customer engagement and devise an effective marketing strategy, Aparna et al. (2019) scrutinized the usage of mobile wallets in India. Their research demonstrates that customers predominantly utilize mobile wallets to recharge, book movie tickets, and make transportation reservations. Semerikova (2019) pinpointed that attribute like style, transaction speed, and instant cashback could significantly drive customer engagement with mobile wallets. On the other hand, a case study was undertaken by Lo et al. (2021) to create a mobile wallet that caters to the requirements of the local populace in Canada and to develop effective strategies for customer engagement and ensure a successful product launch.

Boosting mobile wallet services requires user awareness, making it a crucial factor. The evaluation of consumer perception towards mobile wallets was conducted by Mathiraj et al. (2019) using the Hendry Garret Ranking tool. The study aimed to identify customer perceptions, challenges, and satisfaction levels. The service quality of mobile wallets that are commonly utilized for online shopping was evaluated by Budiarani et al. (2021) using a Kano Model. The satisfaction map generated by the study indicated that service providers should concentrate on enhancing the elements located in the indifferent quadrant to enhance customer satisfaction. Additionally, the impact of risk perception and product knowledge on the satisfaction of mobile wallet users was investigated by Foster et al. (2022), and their results revealed a significant and positive influence.

In their research, George & Sunny (2022) introduced a proposed model that included the situational influence of COVID-19 and a promotional offer to the classic TAM. The study found that both the COVID-19 situational factors and satisfaction had a significant effect on users' intentions to continue using mobile wallets. Meanwhile, Okonkwo et al. (2022) examined the mobile wallet perception in Cameroon, a financial system that relies heavily on cash-based transactions. They analyzed the data using SEM and found that contactless financial transactions may differ from customers' lifestyles in cash-based economies.

To attract mobile wallet owners, one effective strategy these companies employ is to promote exclusive offers through social media platforms while also utilizing them to manage customer relationships and advertise their services (Grover et al., 2017). At the same time, they could quickly increase their popularity and acquire new customers (Hoang & Le, 2020). Grover & Kar (2020) conducted a study analyzing social media sharing to explore mobile wallets' service advertisement and customer dynamics. They discovered that social-based sharings, entertainment, remuneration, and information are valuable for customer acquisition. The study also recommended that firms expand their network size and periodic campaigning.

Lim et al. (2022) investigated the impact of monetary gifts and their innovative function on mobile wallet usage. The study found that the gift function could promote several positive outputs, indicating its potential as a marketing strategy. By examining social media platforms, Teng & Khong (2021) used text mining methodology to understand mobile wallet user behavior. The research found that rewards, cashback, and promotional

campaigns attract customers. Lastly, Aji & Adawiyah (2021) conducted a study to examine the ways how mobile wallets stimulate young customers to spend money. The study's outcomes indicated that young users of mobile wallets are influenced by several key factors, including promotions, perceived easiness, perceived self-control, and the perception of having more money.

2.2.2.3. Competitiveness

Mobile wallets have emerged as a crucial tool for businesses to gain a competitive advantage by leveraging their sustainable aspects. One significant contribution is the reduction of paper-based transactions and the subsequent positive impact on the environment. Mobile wallets also offer customers a secure and convenient payment option, enhancing their trust and loyalty toward the business. Additionally, mobile wallet usage can lead to business cost savings, reducing the need for physical cash handling and associated costs. The availability of mobile wallets on multiple devices, along with features such as real-time transaction tracking and personalized offers, can enhance customer experience and satisfaction. Overall, mobile wallets' sustainable aspects offer businesses a path to profitability while contributing to environmental sustainability, customer satisfaction, and loyalty, thereby increasing their competitiveness in the market.

In order to gain a competitive advantage, service providers should prioritize the quality of their mobile wallet services. According to Kapoor et al. (2020), ten dimensions can be used to measure service quality. Companies can prioritize these drivers by applying a Fuzzy TOPSIS approach and developing effective marketing strategies. Six critical service quality dimensions for mobile wallets were identified by Kapoor et al. (2021), which encompass accessibility, convenience, responsiveness, security and reliability, aesthetics, and information quality. To assess and rank the different mobile wallet alternatives in India, they employed the Fuzzy TOPSIS approach. Ilankumaran (2019) underscored the benefits of Fintech approaches, particularly mobile wallets, in removing paper-based banking transactions. Using a time-series technique, Kumar et al. (2022) examined the endurance of mobile wallet adoption throughout the COVID-19 pandemic and discovered that it had accelerated during that period. Policymakers should therefore focus on enhancing marketing strategies, infrastructure, regulation, and incentives to promote the continued use of mobile wallet services post-pandemic.

Mobile wallets offer several advantages over traditional payment services, such as instant money transfer without cash, perceived ease of use, transaction security, and privacy. Nair & Bhattacharyya (2019) found that customers are motivated to use mobile wallets due to their innovative and sustainable features. However, Al-Badi et al. (2022) have identified several obstacles to the sustainable use of mobile wallets, such as insufficient knowledge, worries about security, limited merchant acceptance, and inadequate financial assistance. Bagla & Sancheti (2018) also noted that the gap between customer expectations and satisfaction levels could challenge the sustainability of mobile wallets.

Two critical factors highlighted by Rana et al. (2022) as implementation challenges for sustainable mobile wallet usage are customers' perception of the value of ownership, and the absence of strong regulatory compliance. In their study, Kumar et al. (2021) employed Main Path Analysis to identify the crucial domains for firms to concentrate on to gain a competitive positioning in the expanding mobile wallet market. Specifically, the study highlighted mobile wallet services, payment technology, financial transaction systems, and payment selection systems as key technological trajectories to consider.

Furthermore, a SWOT analysis was carried out to evaluate the viability of mobile wallets in Malaysia, revealing that the absence of infrastructure and cyber-attacks posed significant weaknesses and threats (Alam et al., 2021). To succeed in the mobile wallet market, companies must address these concerns and capitalize on their strengths and opportunities by devising effective strategies.

The adoption of mobile wallets drives the trend toward cashless transactions and contributes to economic welfare. Sarika & Vasantha (2019) suggest that the growth in mobile wallet usage is aided by technological advancements that enhance mobile wallet user intentions. In their study, Nurcahyo & Putra (2021) employed the Technology-Organization-Environment (TOE) framework along with the TOPSIS and AHP methodologies to pinpoint barriers that impede collaborative decision-making between service providers and e-commerce. According to their findings, offering mobile wallet payments is essential for staying competitive in the e-commerce industry. Along with this, having a solid network, cooperation, management commitment, and expertise were also identified as essential factors for success. The banking industry gained tremendous benefits from the widespread adoption of smartphones and internet access. With the

emergence of mobile wallet technology, internet banking use and ATM transactions are on the rise, leading to a gradual move away from traditional in-person branch banking (Boro, 2015). Investigating strategies for how to gain a competitive advantage for retail banks, Omarini (2018) cited that mobile wallet is crucial in helping banks adopt a customer-centric approach.

2.2.2.4. Security and Privacy

Security and privacy are critical considerations for mobile wallet usage. With the growth of mobile wallet adoption, there has been an increasing focus on ensuring the security of mobile wallet transactions. Using mobile wallets involves exchanging sensitive personal and financial information, and any security breach can have severe consequences for the users. Therefore, mobile wallet providers must implement robust security measures such as encryption, tokenization, biometric authentication, and secure networks to protect user data and prevent unauthorized access. Additionally, privacy concerns may arise when users share personal information with mobile wallet providers. Therefore, mobile wallet providers must ensure transparent policies regarding collecting, using, and sharing user data. Ensuring the security and privacy of mobile wallet transactions is crucial for building user trust and driving further adoption of this technology.

The Know Your Customer (KYC) process has recently undergone changes and has various issues, such as poor customer experience, security concerns, low efficiency, and data protection. Ensuring customers can access KYC-related documents and retain control over their digital assets is paramount. Hassan & Shukur (2021) suggested prioritizing security when designing authentication for mobile wallet owners. This is particularly important due to threats such as SIM swapping, app cloning, and KYC verification attacks, which can influence the mobile wallet shoppers' perceived security. Schlatt et al. (2021) proposed that the mobile wallets' blockchain-based infrastructure facilitates customer digital identity management through the creation and cryptographic key storage. Furthermore, this infrastructure empowers financial institutions to scrutinize suspicious consumer behavior and identify fraudulent activities closely. In order to alleviate customers' security apprehensions, Kavitha et al. (2022) proposed a queuing model that harnesses the capabilities of blockchain technology, such as notifying participants and verifying signatures when records are modified.

The escalating intricacy of the worldwide digital environment introduces new hazards, such as cyberattacks and possible misuse of data, which can undermine customer trust and tarnish an organization's image due to privacy concerns. Researchers have suggested several models evaluate the compliance of mobile wallet considering the General Data Protection Regulation (GDPR). Several studies (Akanfe et al., 2020; Akanfe et al., 2021) highlighted the significance of country-level data protection practices in appraising country-level risk assessment. The study conducted by Iqbal et al. (2020) investigated the use of fingerprint verification technology in mobile wallets and discovered that elderly individuals comprehend biometric verification technology as an insecure method for purchasing goods and services, raising privacy concerns. Akanfe et al. (2021) employed a design science approach to examine the applications for mobile wallet privacy policies across different countries and produce financial inclusion scores.

The majority of the existing literature has concentrated on the adoption of technology, employing behavioral theories and acceptance models to understand the shopping patterns of customers. In order to aid in this effort, researchers have devised concepts to investigate users' perceptions and the challenges they encounter while utilizing mobile wallet technology.

2.3. Technology Acceptance Theories and Models

In the present-day retail industry, technological advancements have revolutionized the shopping experience for customers. Adopting technology has become crucial for retailers to improve their business operations and provide a seamless shopping experience for their customers. Understanding the importance of customer acceptance of technology has become critical for the retail industry to stay competitive. Therefore, several technology acceptance theories and models have been developed to investigate shopping intentions in retail.

2.3.1. Diffusion of Innovation Theories

Everett Rogers first proposed the Diffusion of Innovations (DOI) theory in 1962 as a framework for understanding how innovations are adopted and diffused within a society or organization (Figure 2.5). Since its initial development, the DOI model has undergone several revisions and extensions.

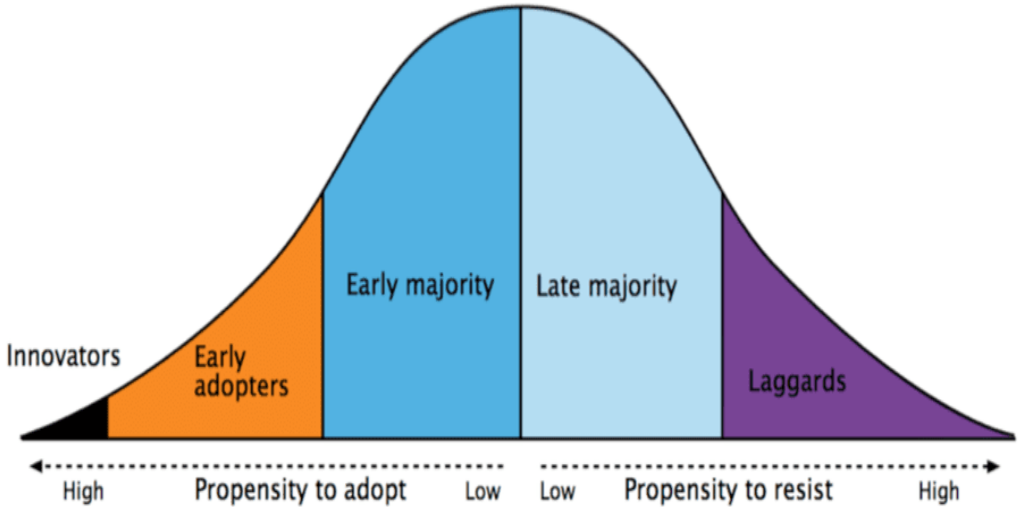


Figure 2.5 DoI model (Rogers, 1962).

The DOI model includes five distinct adopter categories. Although most of the population falls within the middle range, it is crucial to comprehend the target population's characteristics. Diverse strategies are employed to attract the various adopter categories (Rogers, 2003):

- Innovators: These individuals are enthusiastic about being the first to attempt innovations, frequently venturesome, and interested in novel ideas. There is no need to entice them as they are eager to try new things. They are willing to take risks and often develop new concepts.
- Early Adopters: This group represents opinion leaders who relish taking on leadership roles and actively pursue opportunities for change. They are already aware of the necessity for change and, as such, readily embrace new ideas. Strategies such as how-to manuals and implementation information sheets can be employed to attract early adopters as they do not need convincing.
- Early Majority: While not typically leaders, these individuals tend to adopt new ideas ahead of the average person. However, they require evidence that the innovation works before embracing it. To persuade this group, showcasing success stories and evidence of the innovation's effectiveness can be beneficial.
- Late Majority: This category is often skeptical of change and only adopts innovations after the majority has tried them. To appeal to this group, providing information about how many other individuals have tried and successfully adopted the innovation is effective.

- Laggards: This group is generally resistant to change and can be the most challenging group to persuade. Practical approaches to engage this demographic may involve presenting compelling statistics, utilizing fear-based messaging, or leveraging the influence of individuals from other adopter groups.

The DOI model has undergone several revisions and extensions over time to better account for the complex factors that influence the adoption and diffusion of innovations. These modifications have helped to improve the model's explanatory power and applicability to different contexts. Some notable developments in the history of the DOI model:

- Rogers (1983) proposed an extension of the DOI model known as the Five Characteristics of Innovations (FCI) model, which added five new innovation attributes that influence their adoption: complexity, relative advantage, observability, trialability, and compatibility.
- Rogers (1995) proposed an extension of the DOI model known as the Diffusion Network model, which added a new construct: communication channels. This new construct aimed to capture the impact of social networks and communication patterns on the diffusion of innovations.
- Damanpour & Schneider (2006) proposed an extension of the DOI model known as the Configuration Model, which added a new construct: innovation system configuration. This new construct aimed to provide a more comprehensive framework for understanding the complex interactions between innovation attributes, adoption processes, and organizational contexts.
- Horsky & Simon (2015) proposed an extension of the DOI model known as the Continuous Time Innovation Diffusion Model, which added a new construct: time. This new construct aimed to capture the impact of time-related factors, such as innovation speed and market dynamics, on the diffusion of innovations.

The DoI model proposes that the adoption and diffusion of technology follow a predictable pattern. According to the model, innovation is initially adopted by a small group of "innovators," followed by "early adopters," "early majority," "late majority," and finally, "laggards." The model focuses on factors that influence the diffusion of innovation, such as the characteristics of the innovation, the communication channels

used to promote the innovation, and the social system in which the innovation is adopted. In contrast, the TAM and UTAUT models focus on individual-level factors influencing users' acceptance and adoption of technology.

2.3.2. Theory of Reasoned Action and Theory of Planned Behavior

Martin Fishbein and Icek Ajzen, in the late 1970s, originally proposed the Theory of Reasoned Action (TRA), which suggests that an individual's intention to perform a behavior is influenced by their attitude towards the behavior and subjective norms (Fig. 2.6). In retail, TRA has been used to investigate customers' intention to adopt technology in their shopping experience. TRA was later extended to the Theory of Planned Behavior (TPB) in the early 1990s.

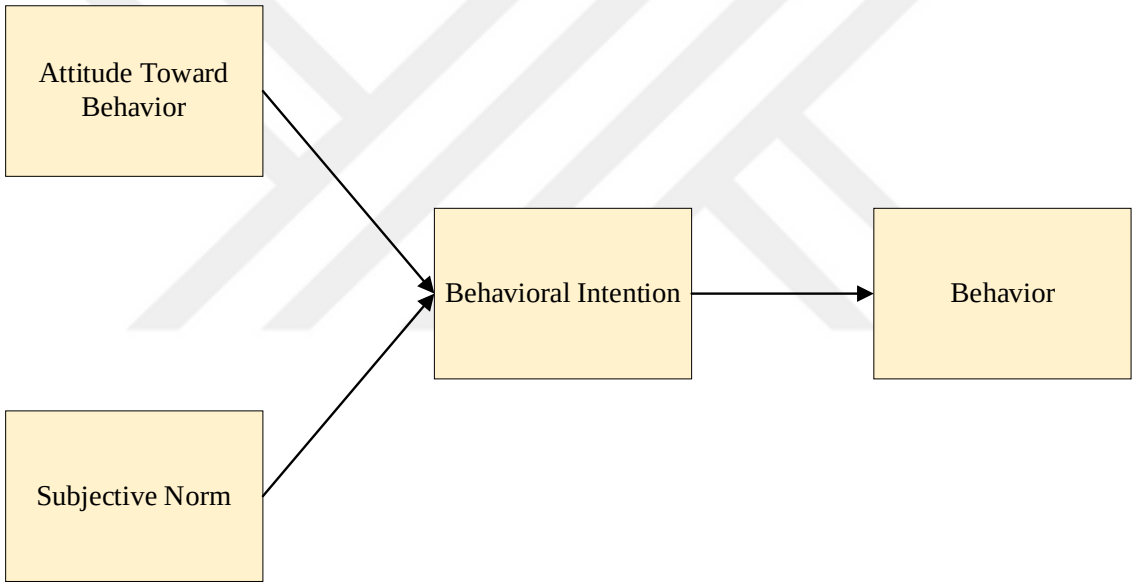


Figure 2.6 TRA model (Fishbein & Ajzen, 1975).

Ajzen introduced TPB in 1991, which extends TRA by including perceived behavioral control as an additional determinant of behavior (Figure 2.7). TPB has been utilized in the retail industry to examine customers' willingness to adopt different technological solutions, including self-checkout systems and mobile payment options.

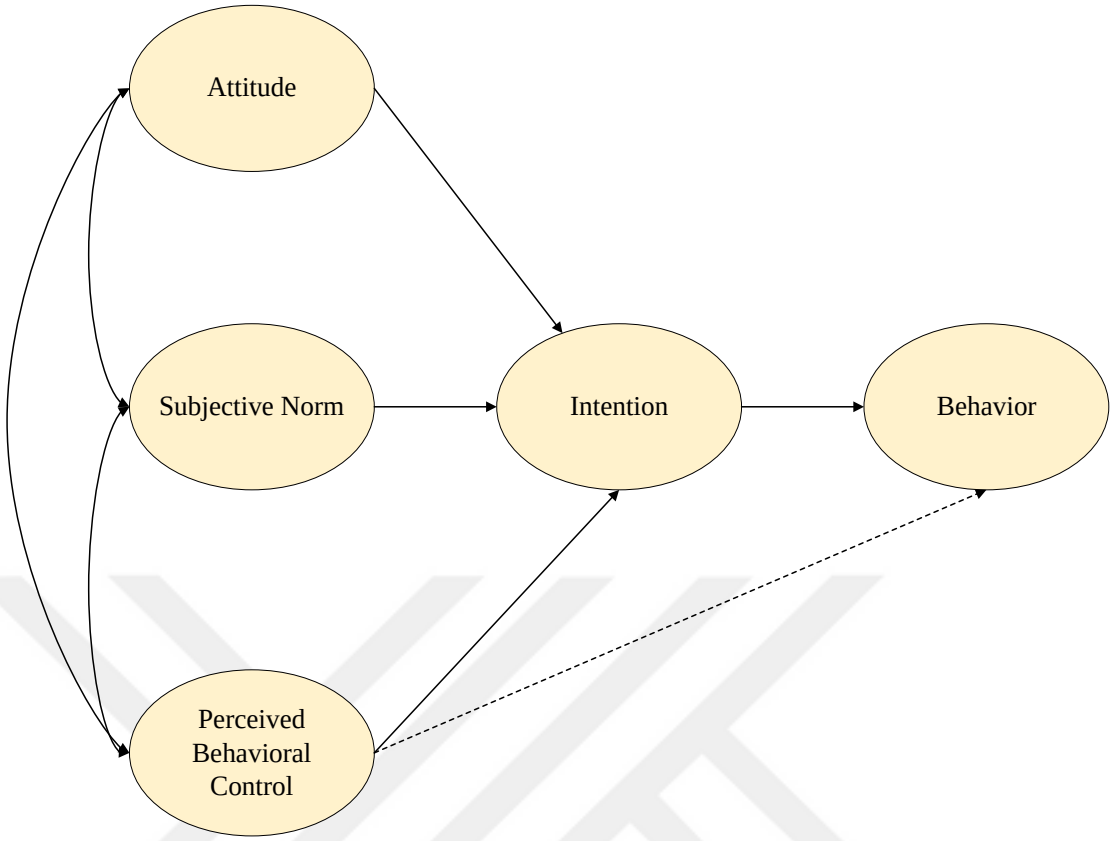


Figure 2.7 TPB model (Ajzen, 1991).

Since their initial development, the TRA and TPB models have undergone several revisions and extensions. Here are some notable developments in the history of these models:

- Ajzen & Fishbein (1980) proposed an extension of the TRA known as the Subjective Norms model, which added a new construct: perceived social norms. This new construct aimed to capture the impact of social influence on behavior.
- Ajzen (1991) proposed an expansion of the TRA known as the TPB, which added two new constructs: perceived behavioral control and intentions. The TPB aimed to account for the influence of perceived control over behavior, attitudes, and social norms.
- Sheppard et al. (1988) proposed an extension of the TRA known as the Triandis model, which added a new construct: attitude toward the act. This new construct aimed to capture the impact of the specific behavior being studied on attitudes and behavior.

- Armitage & Conner (2001) proposed an extension of the TPB known as the Extended Theory of Planned Behavior (ETPB), which added three new constructs: past behavior, anticipated regret, and self-identity. The ETPB aimed to provide a more comprehensive framework for understanding and predicting behavior.

Researchers examining the retail industry have employed the TRA to analyze the shopping intentions of tech-oriented customers. Ajzen & Fishbein (1980) applied the TRA to various domains, including consumer behavior in retail settings. This theory proposes that consumers' behavior is influenced by their intentions, which are shaped by their attitudes and subjective norms. Chen & Yeh (2005) used the TRA to investigate how consumer knowledge affects their intentions to process electronic word-of-mouth (eWOM) messages through online reviews. Their findings indicated that attitudes towards eWOM, behavioral control perception, and subjective norms are crucial factors that affect consumers' intentions to process eWOM messages.

Additionally, Grewal et al. (1998) studied the effects of price-comparison advertising on consumers' perceptions of acquisition value, transaction value, and behavioral intentions in retail settings. Their research demonstrated that consumers' attitudes towards price-comparison advertising, subjective norms, and perceived behavioral control play significant roles in their intentions to purchase products based on price-comparison advertising. Furthermore, Chen et al. (2019) used the TRA to examine consumers' inclination to use mobile shopping applications. They combined the TRA with the TAM and the DOI to investigate the impacts of attitudes, subjective norms, and perceived behavioral control on consumers' intentions to use mobile shopping applications.

Researchers have also employed the TPB in the retail industry to examine shopping intentions. For instance, Venkatesh & Morris (2000) utilized TPB to explore the factors that impact consumers' intentions to use self-service technologies in retail stores. Their study revealed that attitudes, subjective norms, and perceived behavioral control play crucial roles in determining consumers' willingness to use such technologies. Similarly, Lwin et al. (2008) used TPB to investigate the factors influencing consumers' intentions to use credit and debit cards in retail stores. The study identified perceived behavioral control, attitudes, and subjective norms as the key factors affecting consumers' intentions

to use these payment methods. In another study, Mattila & Wirtz (2008) used TPB to investigate the factors that influence consumers' intentions to make impulse purchases in retail stores. They found that subjective norms, perceived behavioral control, and attitudes were important factors in determining customers' intention to make such purchases.

Lastly, Kim & Park (2019) utilized TPB to examine the factors that influence consumers' intentions to purchase restaurant food based on recommendations from food bloggers. The study revealed that attitudes, subjective norms, and perceived behavioral control were significant factors in determining consumers' willingness to purchase restaurant food based on recommendations from food bloggers.

TRA and TPA models highly focus on individual attitudes and beliefs toward a behavior, while TAM and UTAUT models focus on factors influencing technology adoption and usage. However, there is some overlap between the models, as they all involve examining individual beliefs and intentions as predictors of behavior or technology adoption.

2.3.3. Technology Acceptance Model

Fred Davis (1986) first proposed the Technology Acceptance Model (TAM) as a framework for understanding how users adopt and use new technologies (Figure 2.8). Since its initial development, the TAM model has undergone several revisions and extensions. Some notable developments in the history of the TAM model:

- Davis (1989) proposed an extension of the TAM model known as TAM2, which added a new construct: the perceived usefulness of the technology. This new construct aimed to provide a more comprehensive framework for understanding users' motivations to adopt and use new technologies.
- Venkatesh & Davis (2000) proposed an extension of the TAM model known as the Unified Theory of Acceptance and Use of Technology (UTAUT), which integrated several other technology adoption and use models. The UTAUT model added several new constructs, including performance expectancy, effort expectancy, social influence, and facilitating conditions.
- Venkatesh et al. (2012) proposed an extension of the UTAUT model known as UTAUT2, which added a new construct: hedonic motivation. This new construct

aimed to capture the impact of users' emotional and experiential responses to new technologies on their adoption and use.

- Venkatesh and Bala (2008) proposed an extension of the UTAUT model known as the Technology Acceptance Model 3 (TAM3), which integrated several other technology adoption and use models. TAM3 added several new constructs, including subjective norms, perceived enjoyment, and perceived ease of use.

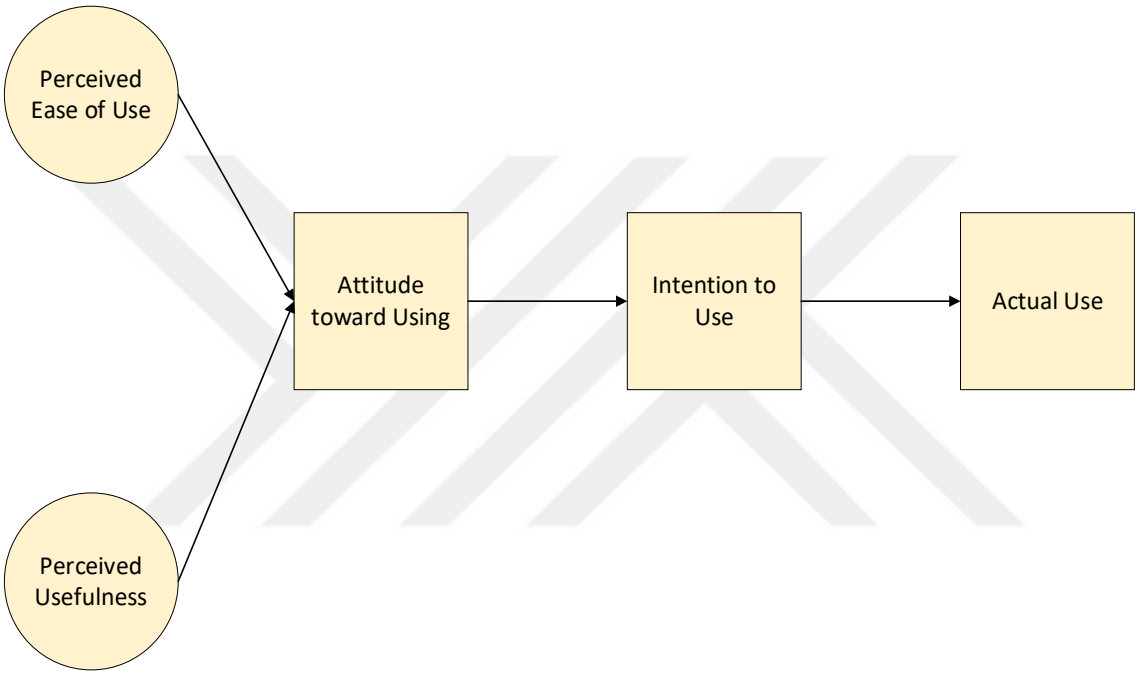


Figure 2.8 The Technology Acceptance Model (Davis, 1986).

The TAM model is a widely-used model in consumer behavior that helps explain how and why consumers adopt new technology. The TAM model is particularly relevant for understanding the retail industry and shopping intentions because it can help shed light on how consumers decide whether to adopt new shopping technologies, such as online shopping platforms, mobile apps, or virtual reality experiences.

The TAM model proposes that two primary factors influence consumers' adoption of new technologies: perceived usefulness and perceived ease of use. Perceived usefulness refers to the extent to which consumers believe that new technology will help them achieve their goals or solve a problem they are currently facing. Perceived ease of use refers to the extent to which consumers believe that new technology will be easy to use and understand (Wu et al., 2019)

Attitudes are indirectly included in Davis's TAM, as they can influence the two primary constructs of the model, perceived usefulness and perceived ease of use. Attitudes can be defined as an individual's positive or negative evaluation of a technology or behavior (Wang et al., 2018).

According to the TAM, an individual's attitude towards using technology can be influenced by their perceptions of the technology's usefulness and ease of use. If the individual perceives the technology as useful and easy to use, they are more likely to have a positive attitude towards using it. On the other hand, if the individual perceives the technology as useless or difficult to use, they are more likely to have a negative attitude towards using it (Sanchez-Prieto et al., 2021).

In the context of the retail industry and shopping intentions, the TAM model suggests that consumers are more likely to adopt new shopping technologies if they believe that these technologies will be useful in helping them to find and purchase the products they want and if they find the technologies to be easy to use and navigate. For example, suppose a consumer is looking for a specific product that is not available in their local store. In that case, they may be more likely to adopt an online shopping platform if they believe it will help them find the product quickly and easily (Wang et al., 2018).

Retailers can benefit significantly by applying the TAM model as it can assist them in designing and marketing shopping technologies that are more likely to be adopted by consumers. By emphasizing their new technologies' usefulness and ease of use, retailers can increase the likelihood that consumers will be willing to try them out and incorporate them into their shopping routines. Furthermore, the TAM model can help retailers identify potential barriers to adoption and address them proactively by providing clear instructions or offering incentives to early adopters.

Several studies have applied the TAM model to examine various factors influencing consumer behavior in retail industry. Wang et al. (2020) explored factors that influence mobile payment technology adoption, while Lee et al. (2019) examined online purchase intention among Malaysian consumers. Kuo et al. (2018) studied the adoption of self-service technologies in retail, and Chen & Li (2017) investigated factors influencing online shopping behavior in China. Tan & Teo (2017) focused on generation Y's online purchase intentions in Malaysia using TAM and perceived risk.

Additionally, Wu & Wu (2020) investigated consumers' intention to use mobile apps for social commerce in retail using TAM. Lu et al. (2020) researched the factors affecting consumers' intention to adopt interactive technologies in retail stores using TAM. Chen et al. (2019) combined TAM and Technology Acceptance and Uses Theory (TAUT) to study virtual reality shopping. Liu et al. (2019) explored the factors that affect consumers' acceptance and use of autonomous delivery robots in the retail industry. Lastly, Wang et al. (2019) investigated the factors influencing young consumers' behavioral inclination to use mobile payment in retail using TAM.

The TAM model focuses on users' attitudes toward using technology and their perceptions of its ease of use and usefulness. It proposes that these factors influence users' behavioral intention to use technology, leading to actual technology use. On the other hand, the UTAUT model expands on the TAM model by incorporating four additional factors: performance expectancy, effort expectancy, social influence, and facilitating conditions. These factors are believed to significantly impact users' intention to use technology and their actual behavior.

In conclusion, the TAM is a theoretical framework for understanding users' acceptance and adoption of technology. Over time, researchers have identified additional factors that can influence user acceptance and adoption of technology, such as perceived enjoyment, discomfort, optimism, innovativeness, and trust.

2.3.4. The Unified Theory of Acceptance and Use of Technology

The Unified Theory of Acceptance and Use of Technology (UTAUT) was proposed by Venkatesh et al. in 2003, building on earlier technology acceptance models such as the TAM, the TRA, and the TPB. The UTAUT model aimed to provide a more comprehensive framework for understanding technology adoption and use by incorporating a broader range of contextual and individual factors (Fig. 2.9).

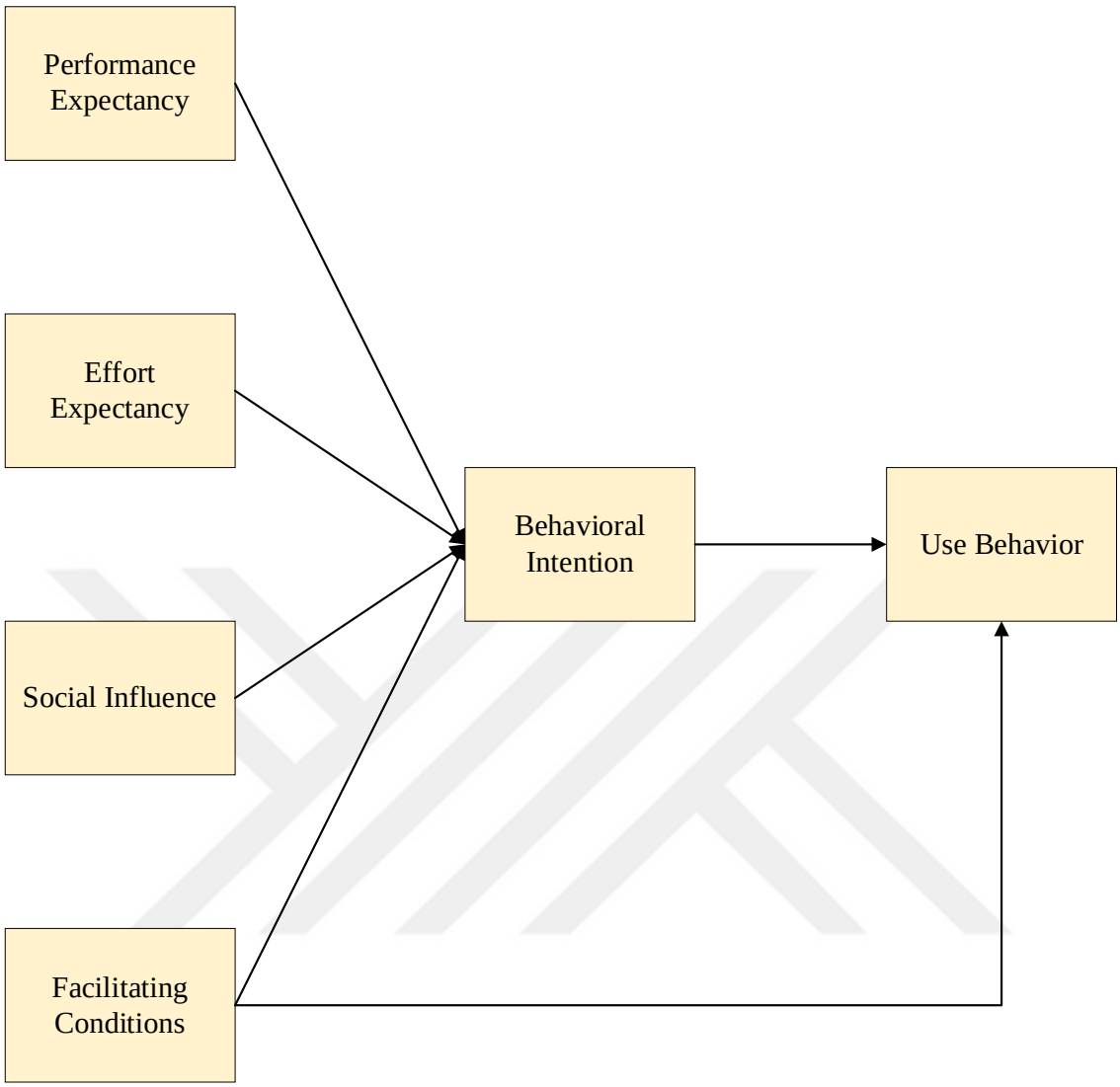


Figure 2.9 UTAUT model (Venkatesh et al., 2003).

UTAUT is a theoretical framework that proposes factors influencing users' behavioral intentions to adopt new technologies. Some of the factors that unify the UTAUT model:

- Performance Expectancy:

  Performance expectancy is a critical factor that unifies the UTAUT model. This refers to the degree to which a user believes that using the technology will help them to perform better. This factor is critical because people are motivated to adopt new technologies that provide them with benefits that they did not have before. Innovations seen as improving performance are more likely to be adopted quickly (Wang et al., 2018).

- Effort Expectancy:

Effort expectancy is another important factor that unifies the UTAUT model. This refers to the degree to which a user believes that using the technology will be easy and free of effort. People are more likely to accept new technologies that are easy to understand and use and that do not require significant changes to their daily routines. Innovations perceived as easy to use and requiring minimal effort are more likely to be adopted quickly (Park et al., 2018; Wang et al., 2018).

- Social Influence:

Social influence is another important factor that unifies the UTAUT model. This refers to the degree to which a user believes that important others, such as friends or colleagues, think they should use the technology. The influence of others on the user's intention to use the technology is an important factor that unifies the model. Users are more likely to adopt new technologies if they believe that significant others believe it is important to do so (Park et al., 2018).

- Facilitating Conditions:

Facilitating conditions are another factor that unifies the UTAUT model. This refers to the degree to which a user believes that they have the necessary resources and abilities to use the technology. Users are more likely to adopt new technologies if they believe that they have the necessary resources and abilities to use them. Innovations that are perceived as controllable are more likely to be adopted quickly (Zhou et al., 2010)

Since its initial development, researchers have proposed several modifications and extensions to the UTAUT model. Here are some notable developments in the history of UTAUT:

- Venkatesh & Bala (2008) proposed an extension of UTAUT known as UTAUT2, which added four new constructs: performance expectancy, effort expectancy, social influence, and facilitating conditions. This revised version of the model aimed to better account for the social and organizational factors that may influence technology acceptance and use.

- Shih et al. (2012) proposed an extension of UTAUT2 known as UTAUT-IT, which added a new construct: IT self-efficacy. This new construct was hypothesized to influence user acceptance and use of information technologies in the workplace.
- Venkatesh et al. (2016) proposed an extension of UTAUT2 known as UTAUT2-S, which added a new construct: security and privacy concerns. This new construct aimed to account for the increasing importance of security and privacy in technology adoption and use.
- Alalwan et al. (2017) proposed an extension of UTAUT2, known as UTAUT2-CS, which added a new construct: customer satisfaction. This new construct aimed to capture the impact of user satisfaction on the continued use of technology.

On the hand, The Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) is a model that explains the factors that influence individuals' behavioral intentions to use technology (Fig. 2.10). The UTAUT2 model builds on the original UTAUT model developed by Venkatesh et al. (2003).

Unlike UTAUT, hedonic motivation is an essential construct in the UTAUT 2 model and can influence individuals' intention to adopt and use technology directly or indirectly through other constructs. It refers to the pleasure or enjoyment that individuals derive from using technology. According to the model, hedonic motivation can influence an individual's intention to use technology either directly or indirectly through other constructs such as effort expectancy and social influence (Venkatesh et al., 2012).

Since its introduction, the UTAUT2 model has been widely studied and improved by various researchers. These researchers and others have made various improvements and extensions to the UTAUT2 model over the years. For instance, Venkatesh et al. (2016) proposed a unified theory that integrates the UTAUT2 model with other technology adoption and uses theories. Al-Gahtani (2017) extended the UTAUT2 model to include trust as an additional factor that affects users' acceptance of e-learning technology.

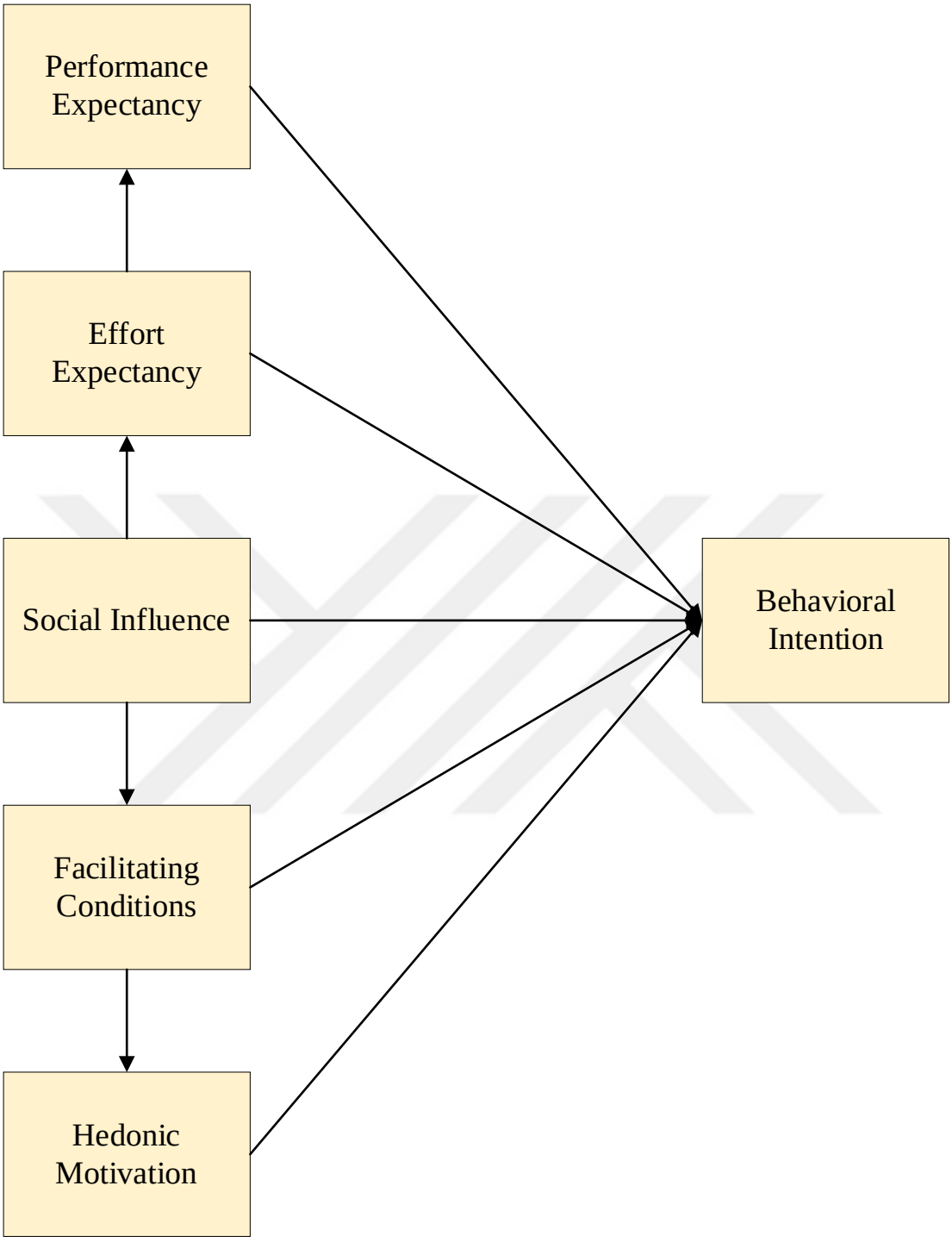


Figure 2.10 UTAUT2 model (Venkatesh et al., 2012).

Additionally, Chuttur (2009) provided an overview of the Technology Acceptance Model, which includes the UTAUT and UTAUT2 models, and discussed the origins, developments, and future directions of these models. Wang & Shih (2009) validated the UTAUT2 model by applying it to an investigation of users' acceptance of information kiosks. Finally, Holden et al. (2018) proposed a theoretical model of health information

technology usage and satisfaction among medical residents, which incorporates the UTAUT2 model as one of its components.

Several studies have utilized UTAUT and UTAUT2 to examine shopping intentions in retail contexts. For example, Raza et al. (2020) explored the adoption of mobile payment services in retail and evaluated the moderating effect of gender differences using UTAUT. Additionally, Alalwan et al. (2017) investigated the influence of social media on consumer buying intentions in the retail context using UTAUT. Lu et al. (2017) used UTAUT to create a customer adoption model for mobile retail payments. Zhou et al. (2017) employed UTAUT to study the factors impacting mobile commerce adoption in retail and proposed a modified UTAUT model. Furthermore, Venkatesh et al. (2016) applied UTAUT to analyze the factors influencing online shopping behavior in retail.

Furthermore, UTAUT was utilized to investigate the factors that affect customers' acceptance of mobile payment services in retail (Xu et al., 2020). Similarly, Hu et al. (2019) applied UTAUT to investigate the determinants of customer willingness to utilize smart retail technologies in the United States and China. Shen et al. (2018) used UTAUT to investigate the factors influencing the adoption of mobile shopping among older people in the retail setting. Yu et al. (2018) utilized the UTAUT framework to evaluate how social media affects online purchase intention, with perceived trust and perceived value acting as mediating factors. Chen et al. (2017) explored the factors influencing consumers' intention to use virtual reality shopping in their study using UTAUT, with innovativeness as a moderating factor.

In their study, Alalwan et al. (2020) utilized the UTAUT2 model in the retail industry to examine the determinants of consumer acceptance of self-service technologies. Similarly, Zhang et al. (2019) applied UTAUT2 to investigate the adoption of omnichannel retailing and the role of consumer experience. In the context of mobile shopping applications, Alalwan et al. (2018) employed UTAUT2 to explore the factors influencing adoption. Chen et al. (2018) used UTAUT2 to examine the impact of perceived risk on consumer adoption of mobile payment services in retail. Li et al. (2018) investigated the moderating effect of gender on the factors that affect mobile payment adoption in the retail context using UTAUT2.

2.3.5. Technology Readiness Index

The Technology Readiness Index (TRI) was initially developed by Parasuraman (2000), who proposed that an individual's readiness to accept new technology was based on their attitudes. The original TRI consisted of four dimensions: optimism, innovativeness, discomfort, and insecurity (Fig. 2.11).

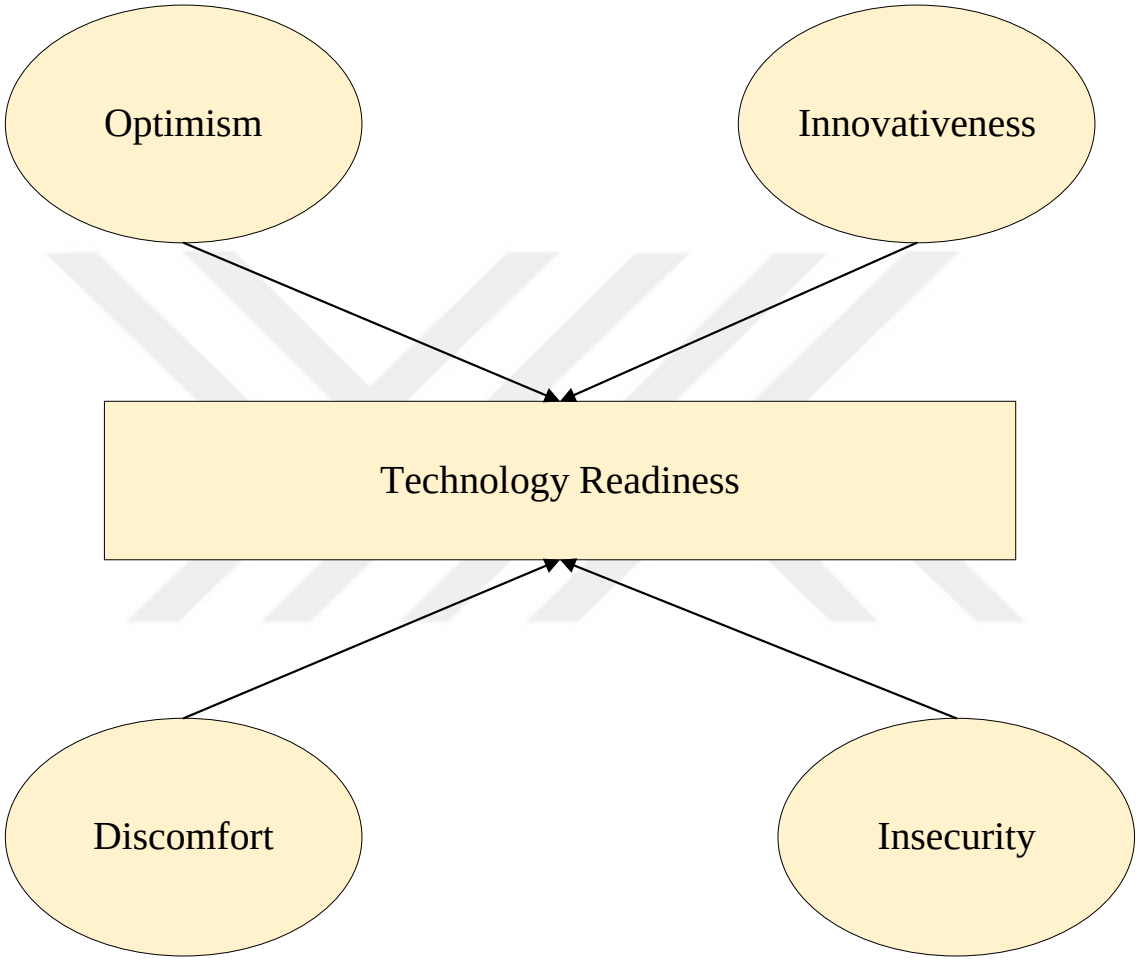


Figure 2.11 TRI model (Parasuraman, 2000).

- Optimism: Optimism refers to the extent to which an individual believes that new technology will benefit them. Optimism is characterized by hopefulness, excitement, and enthusiasm about new technology. Individuals scoring high on this dimension tend to have positive attitudes toward technology and are optimistic about its potential benefits (Parasuraman, 2000). Furthermore, optimism is a significant predictor of technology acceptance and use in various studies (e.g., Karahanna et al., 2006; Venkatesh et al., 2003).

- Innovativeness: Innovativeness refers to the extent to which an individual is willing to try new technology before others do it. Innovativeness is characterized by a willingness to take risks, a desire to be a leader, and a desire for novelty. Individuals who score high on this dimension tend to be early adopters of new technology and are willing to take risks to try out new products or services (Parasuraman, 2000). On the other hand, innovativeness is a significant predictor of technology adoption and uses in various studies (e.g., Agarwal & Prasad, 1997; Rogers, 1995).
- Discomfort: Discomfort refers to the extent to which an individual feels uncomfortable or uncertain about using new technology. Discomfort is characterized by uncertainty, anxiety, and fear about new technology. Individuals who score high on this dimension tend to be hesitant to try out new technology and may feel anxious or intimidated by it (Parasuraman, 2000). Discomfort is a significant barrier to technology adoption and uses in various studies (e.g., Venkatesh et al., 2003; Webster & Martocchio, 1992).
- Insecurity: Insecurity refers to the extent to which an individual lacks confidence in their ability to use new technology. Insecurity is characterized by self-doubt, inadequacy, and fear of failure. Individuals who score high on this dimension may lack the skills or knowledge necessary to use new technology effectively (Parasuraman, 2000). Also, insecurity is a significant barrier to technology adoption and uses in various studies (e.g., Agarwal & Prasad, 1998; Venkatesh et al., 2003).

TRI has been widely used in various contexts to measure individuals' technology readiness and has been found to have good psychometric properties. Since its development, the TRI has been used in many studies to measure individuals' technology readiness, and it is a valuable tool for predicting technology adoption behavior. Researchers have also explored the relationship between technology readiness and various outcomes, such as technology acceptance, use, and performance. Lin et al. (2007) proposed a new model called the Technology Readiness and Acceptance Model (TRAM) that combines elements of the TAM and TRI (Fig. 2.12). According to the authors, the TRAM model has offered a more comprehensive understanding of technology adoption behavior than previous models and could guide the development of more effective

marketing strategies for promoting new technologies.

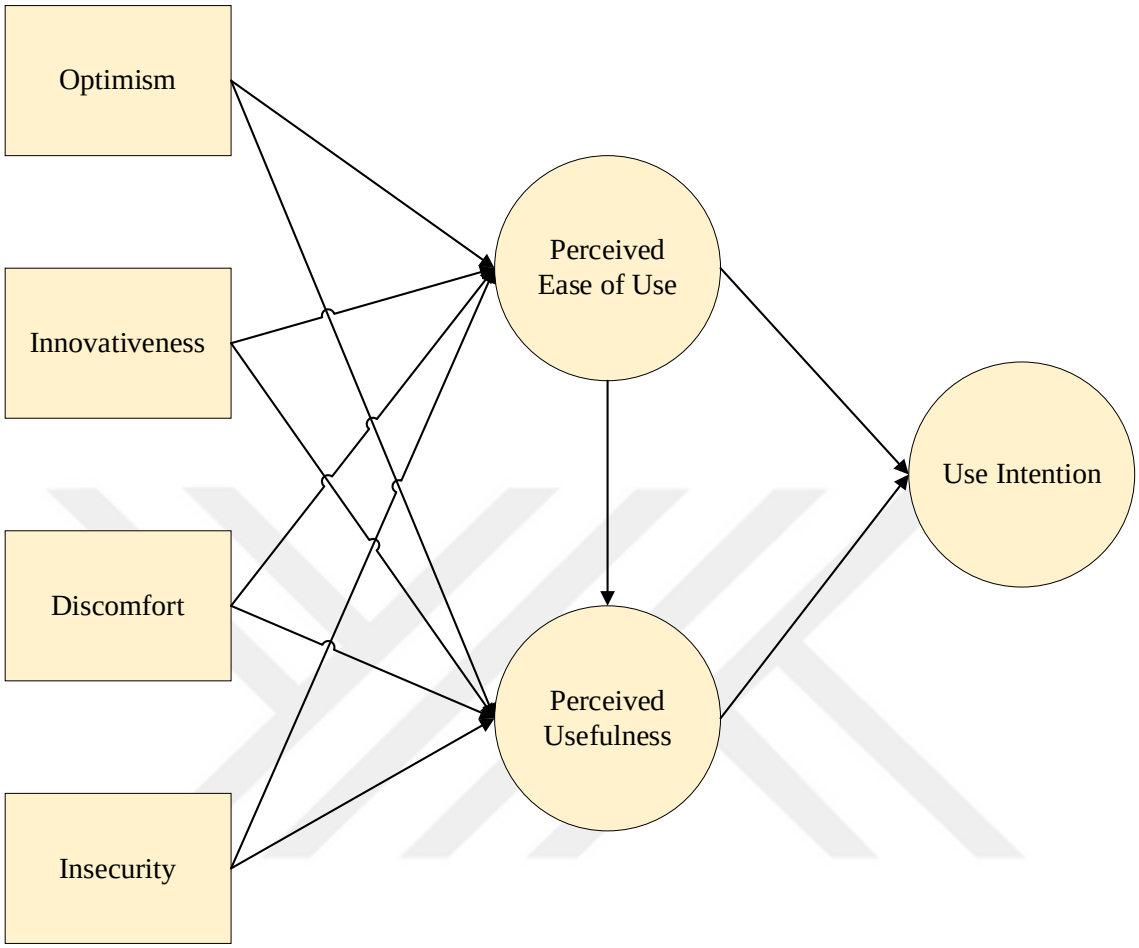


Figure 2.12 TRAM model (Lin et al., 2007).

3. PROPOSED MODEL

A comprehensive and proposed research model for determining customers' intention to use was created using TRAM and context-specific constructs. When the literature was scanned for mobile wallets, it was seen that a version of the TRAM model using context-specific variables such as transaction speed, trust, and perceived enjoyment was not investigated (Hopalı et al., 2022). Insecurity, one of the constructs of technology readiness in the TRAM model, was excluded from this study. On the other hand, other technology readiness constructs, such as innovativeness, optimism, and discomfort, are used in the model. The main reason is to investigate the positive effect of the trust construct on attitude and not cause conflict with insecurity (Fig. 3.1).

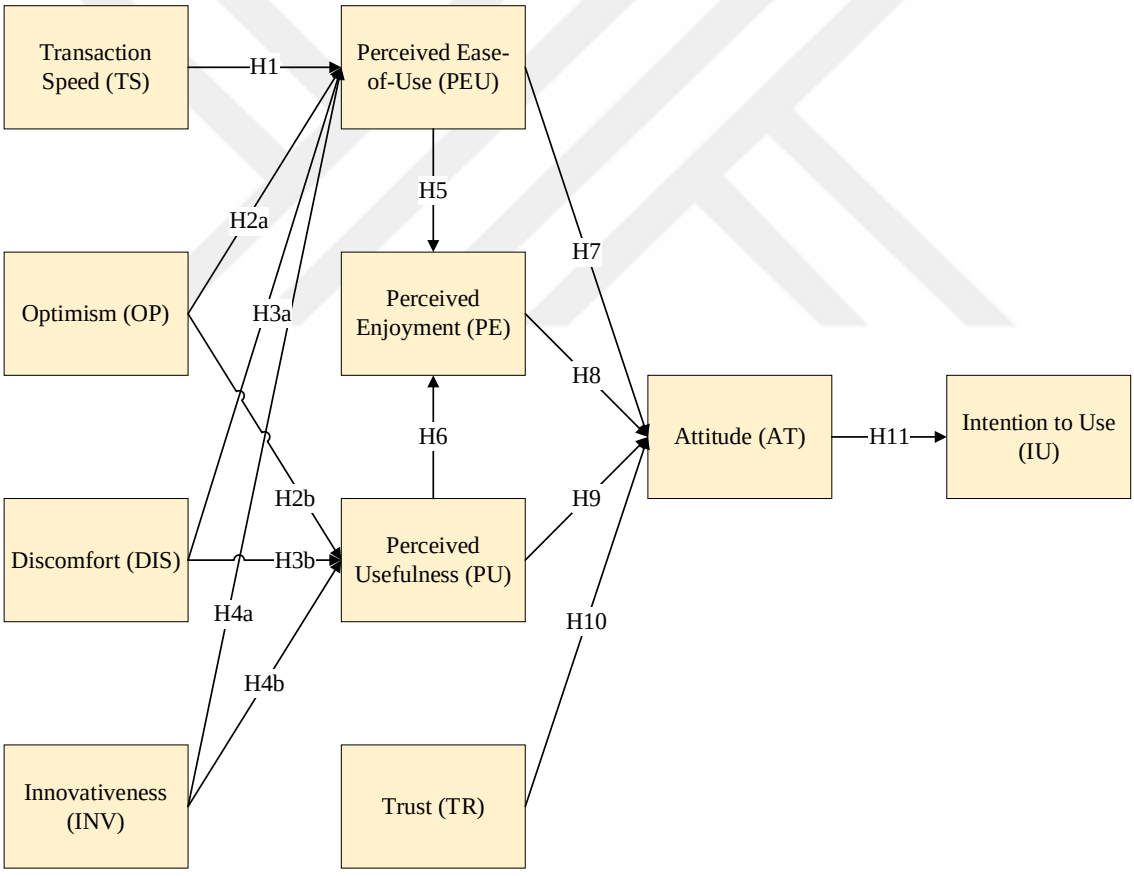


Figure 3.1 Proposed model.

The transaction speed factor in technology acceptance refers to the perception of individuals that a particular technology can provide faster and more efficient transactions compared to existing alternatives. This factor is closely related to the positive viewpoint

factor, as individuals with a positive attitude toward technology are more likely to appreciate the benefits of faster transactions. Several studies have shown that transaction speed is an essential determinant of technology acceptance. Individuals who perceive technology as faster and more efficient are more likely to adopt it. For example, a study by Chang & Chen (2021) found that quick transactions significantly affected behavioral intention to use new technology.

Transaction speed is closely related to perceived ease of use, as individuals who perceive technology as faster and more efficient are more likely to find it easy to use. According to Pantano et al. (2017), transaction speed positively affects perceived ease of use, and individuals who perceive technology as fast and efficient are more likely to adopt it. Yan et al. (2021) found that perceived ease of use was a significant predictor of intention to use mobile wallets with QR codes and that perceived usefulness and perceived ease of use were both influenced by transaction speed. Similarly, a study by Teo et al. (2015) showed that transaction speed and transaction convenience had a significant effect on perceived ease of use (PEU) of mobile payment technology acceptance. Thus, hypothesized as below:

H1. TS regarding smart retail technology positively affects the PEU of mobile wallets in offline and online retail channels.

The optimism factor of the TRAM model refers to individuals' positive outlook toward technology, which stems from their recognition of its potential to enhance flexibility, and efficiency. This factor also entails a willingness to adopt new technologies that become available in the market, as observed in the studies by Parasuraman & Colby (2015) and Liljander et al. (2006). Customers who exhibit a positive attitude towards technology are more likely to use and accept new technologies, as noted by Shin & Lee (2014), and Humbani & Wiese (2018).

The optimism factor of the acceptance model influences users' decisions to adopt new technologies. According to studies by Kim & Chiu (2019), Roy et al. (2018), and Chen & Lin (2018), the optimism factor is associated with Perceived Ease of Use (PEU). This, in turn, affects PEU and influences customers' inclination to adopt the technology. In this context, customers with a positive attitude toward technology are more inclined to adopt mobile wallets in shopping (Yan et al., 2021). Hence, it is proposed:

H2a. OP regarding smart retail technology positively affects the PEU of mobile wallets in offline and online retail channels.

Individuals who are optimistic about new technology may be more likely to perceive mobile wallets as useful, given their belief that technology can offer convenience and efficiency (Pillai et al., 2020). A mobile wallet cultivates a favorable perception and confidence in its usefulness within the consumer's mindset. Existing literature has identified the significant impact of optimism on the perceived usefulness (PU) of mobile wallets (Yan et al., 2021; Oh et al., 2014; Kumar & Mukherjee, 2013). Hence, hypothesized as:

H2b. OP regarding smart retail technology positively affects the PU of mobile wallets in offline and online retail channels.

Innovativeness refers to an individual's willingness to try new and innovative products or technologies. Individuals with higher innovativeness tend to exhibit a positive attitude toward new technology and be more prepared to adopt and use it. Innovativeness is a characteristic that is highly valued in today's society (Kotler & Armstrong, 2012). It is the tendency to embrace new technologies and ideas and to be a pioneer in their implementation. Those who possess this trait are often seen as thought leaders and early adopters of innovative products and services. They are not afraid to take risks, explore new possibilities, and always look for ways to improve existing technologies. Innovators are known to challenge conventional thinking and create creative solutions to complex problems. Being an innovator requires a certain level of courage, determination, and willingness to embrace change. It involves the ability to think outside the box and to see things from a different perspective. Innovators need to be more content with the status quo; they constantly look for ways to push the boundaries and create something new and exciting. They are also excellent problem solvers, as they can identify issues and develop innovative solutions to address them (Audretsch et al., 2022).

Furthermore, innovators have a natural curiosity and a thirst for knowledge. They are constantly seeking new information and insights that can help them better understand the world around them. They need to be more content with accepting things at face value and always look for ways to improve existing technologies and systems. In essence, innovativeness is a mindset that drives individuals to explore, experiment, and create to

impact the world positively (Füller et al., 2022).

According to research by Walczuch et al. (2007) and Godoe & Johansen (2012), consumers with an innovative mindset tend to perceive technology as easy to use for a particular task. This situation highlights the importance of innovativeness as a crucial factor that shapes individuals' perception of technology's ease of use. More innovative individuals are more likely to be early adopters of smart retail technologies such as mobile wallets and to have a positive attitude toward their use. They are also more likely to experiment with different mobile wallet options and find them easy to use. The following hypothesis is thus proposed:

H3a. INV regarding smart retail technology positively affects the PEU of mobile wallets in offline and online retail channels.

Individuals with an innovative mindset towards technology are known to possess a good understanding of how technology works and find learning about new advancements interesting. They view technology as a tool that can enhance their daily lives and are more likely to perceive it as useful and valuable. As a result, innovativeness positively affects the perceived usefulness of new technologies (Lin et al., 2007, Kim & Chiu, 2019). Accordingly, mobile wallets are also new innovative technology, so innovativeness is expected to influence the perceived usefulness of shopping. Hence, the following hypothesis is presented for testing:

H3b. INV regarding smart retail technology positively affects the PU of mobile wallets in offline and online retail channels.

Discomfort arises from individuals' apprehension and unease when using new technology. This discomfort can lead to negative impacts on individuals' ability to adopt and integrate new technology into their daily lives. As a result, technology designers and developers must consider the impact of discomfort when creating new products and systems. Addressing the sources of discomfort can help alleviate individuals' apprehension and improve their overall experience with new technology (Seong & Hong, 2022; Martens et al., 2017). Ultimately, this can lead to greater adoption and use of new technology, benefiting individuals and society.

Studies indicate that discomfort can negatively affect individuals' perceived ease of use, which may hinder their willingness to use and learn about new technology. In other words,

when individuals experience discomfort towards new technology, they may find it more difficult to use and interact with it, potentially reducing the perceived ease of use (Martens et al., 2017; Pillai et al., 2020). Thus, it is expected that discomfort negatively impacts the perceived ease of use of mobile wallets.

H4a. DIS regarding smart retail technology negatively affects the PEU of mobile wallets in offline and online retail channels.

Discomfort refers to the unease and apprehension that consumers experience toward technology, as defined by Parasuraman (2000). This concept captures the negative emotions that consumers may have when confronted with new technology, as explained by Pillai et al. (2020). Therefore, technology designers and marketers need to consider the role of discomfort in shaping consumers' perceptions and attitudes toward technology. Addressing and mitigating consumers' discomfort can increase the likelihood of the successful adoption and integration of new technologies into consumers' lives. The prevalence of discomfort is particularly significant in emerging technologies, where unfamiliarity and uncertainty can exacerbate consumers' discomfort. Studies on the impact of discomfort suggest that it can harm the perceived usefulness of new technology, as demonstrated by studies conducted by Kim & Chiu (2019) and Jin (2013). Thus, it is expected that discomfort negatively impacts the perceived usefulness of smart retail technologies such as mobile wallets.

H4b. DIS regarding smart retail technology negatively affects the PU of mobile wallets in offline and online retail channels.

Several factors influence customers' perceived enjoyment of new technologies, and perceived ease of use is one of the significant factors contributing to it. When customers find technology easy to use, they are more likely to enjoy the experience of using it. This consequence is because perceived ease of use reduces cognitive load and increases customers' sense of control over the technology (Huang et al., 2022; Chang & Chen, 2021; George & Sunny, 2021). For instance, if customers find an online shopping website easy to navigate and use, they are more likely to enjoy browsing products and making purchases. Similarly, if customers find a mobile payment app easy to use, they are more likely to enjoy the convenience of making payments without carrying cash or cards.

Moreover, the relationship between perceived ease of use and perceived enjoyment (PE)

of new technologies is mutually reinforcing. When customers enjoy using technology, it can enhance their perceived ease of use by reducing anxiety or frustration. Additionally, customers who enjoy using new technology are more likely to use it frequently and explore its features, which can increase their familiarity and comfort with it (Pantano et al., 2017). Consequently, this can further enhance their perceived ease of use and enjoyment of the technology. Therefore, businesses should focus on designing technologies that are easy to use and provide an enjoyable user experience. By doing so, they can increase customers' perceived ease of use and enjoyment of new technologies, leading to greater adoption and customer satisfaction. Thus, proposed hypothesis is given as below:

H5: PEU is positively and significantly associated with customers' PE of mobile wallets in offline and online retail channels.

The perceived usefulness of new technologies is a critical factor influencing customers' perceived enjoyment. Customers who perceive that new technology can satisfy their needs and help them achieve their goals are more likely to enjoy using it (Natarajan et al., 2018; Rese et al., 2017). For example, if customers perceive an e-learning platform as useful in providing high-quality educational content, they are more likely to enjoy using it for their studies. Similarly, suppose customers perceive a smart home automation system as useful in making daily tasks more accessible and efficient. In that case, they are more likely to enjoy using it to control their home environment.

Furthermore, the relationship between perceived usefulness and perceived enjoyment of new technologies is not a one-way street. When customers enjoy using new technology, it can further enhance their perception of its usefulness (Park et al., 2019; Rese et al., 2020). Customers who enjoy using technology are more likely to explore its features and benefits, which can increase their understanding of its potential usefulness. This increased understanding, in turn, can further enhance their enjoyment of the technology, creating a positive feedback loop between perceived usefulness and perceived enjoyment. Therefore, businesses must focus on designing technologies perceived as useful and providing an enjoyable user experience (Holdack et al., 2022). By doing so, they can increase customers' perceived usefulness and enjoyment of new technologies, leading to greater adoption and customer satisfaction. Moreover, businesses should conduct user

testing and gather customer feedback to understand their needs and preferences better. By incorporating these insights into the design process, businesses can ensure that their technologies are useful and enjoyable for their customers. Thus, the following hypothesis has been proposed:

H6: PU is positively and significantly associated with customers' PE of mobile wallets in offline and online retail channels.

Perceived ease of use determines whether customers adopt new technologies. It refers to how people perceive new technology as easy to use and learn and how effortless it is to integrate into their daily lives (Lee et al., 2019). Various studies have demonstrated that perceived ease of use is a key predictor of technology adoption across different domains. Natarajan et al. (2017) have shown that customers' perceptions of the ease of using mobile shopping apps can influence their adoption of this shopping mode. The ease of using smartphones for mobile shopping significantly influences customers' attitudes toward this shopping behavior. Similarly, in mobile payments, perceived ease of use has been shown to influence customers' attitudes and intentions to adopt such payment systems (Martens et al., 2017).

Furthermore, the advent of AI-powered automated shopping has introduced new ways for customers to interact with technology. Research by Pillai et al. (2020) has demonstrated that perceived ease of use is significantly associated with customers' attitudes and intentions to adopt AI-powered automated shopping systems.

The findings from various studies highlight the importance of designing technologies that are easy to use and learn. Businesses prioritizing designing user-friendly interfaces and intuitive systems can improve customers' attitudes toward new technologies. Therefore, the following hypothesis is proposed:

H7: PEU has a significant and positive relationship with customers' AT towards the adoption of mobile wallets in offline and online retail channels.

Perceived enjoyment is crucial to customers' attitudes toward adopting new technologies. It refers to how people perceive a task using technology as pleasurable, irrespective of its outcomes (Tamilmani et al., 2019). For instance, customers derive pleasure from a shopping experience that is fun and engaging, whether in a physical store or online, due to the applications used.

Thanks to the advent of smart retail technologies, customers can now enjoy a delightful and hassle-free shopping experience. Researchers have highlighted the importance of perceived enjoyment in driving customers' attitudes toward adopting new technologies, including smart retail technologies. Studies by Kahn et al. (2018), Bauer et al. (2018), and Brill et al. (2018) have shown that the use of such technologies enhances customers' enjoyment of the shopping experience.

The positive relationship between perceived enjoyment and customers' attitude toward technology adoption must be considered. Customers are more likely to embrace new technologies if they find them enjoyable. Therefore, businesses that seek to increase customers' adoption of new technologies must prioritize creating enjoyable and engaging experiences that customers will love. This situation can be achieved by leveraging smart retail technologies and designing user-friendly interfaces that cater to customers' preferences and needs. The following hypothesis is proposed based on the discussion above:

H8: PE has a significant and positive relationship with customers' AT towards the adoption of mobile wallets in offline and online retail channels.

Customers' perception of a technology's usefulness has a direct correlation with their willingness to adopt it and develop a positive attitude toward it. Such a positive attitude is likely to lead to increased adoption rates, resulting in the technology's success in the market. Therefore, companies should emphasize the perceived usefulness of new technologies to improve the likelihood of customer adoption. Numerous research studies have established a clear and consistent relationship between perceived usefulness and attitude. Specifically, Singh & Sinha (2020), Chi (2018), and De Luna et al. (2019) have all demonstrated that perceived usefulness is positively associated with attitude.

This thesis is aimed to explore how the perceived usefulness of mobile wallets influences users' intention to use them by examining the mediating role of attitude. In other words, a customer's attitude towards mobile wallets will be influenced by their perception of their usefulness, affecting their intention to use them.

Building on these premises, we put forward the following hypotheses for further investigation:

H9: PU has a significant and positive relationship with customers' AT towards the

adoption of mobile wallets in offline and online retail channels.

The concept of trust is crucial in any interaction, including those involving technology. Trust entails a willingness to be vulnerable to the actions of another party based on the expectation that they will perform an action that is important to the person placing their trust in them. As Huang et al. (2022) suggest, this definition implies that monitoring or controlling the other party is not necessary to establish trust.

In the context of technology, trust is essential in determining consumer expectations of the technology's reliable performance. On the other hand, integrity-based trust emphasizes the social and attitudinal aspects of relationships and is grounded in consumer perceptions of the honesty and motives of the trusted party (Connelly et al., 2018). The importance of trust in shaping customers' adoption of technology cannot be overstated. However, past studies have yet to explore the direct connection between trust and customers' attitudes toward embracing new technologies, as noted by Kaushik et al. (2015) and Chetioui et al. (2021).

Trust in technology can be built by focusing on the technology's positive attributes and meeting user-specific expectations. Factors such as security, reliability, and ease of use are essential attributes that can foster trust in technology (Hartano et al., 2014; Senali et al., 2022; Yang & Ngo, 2023). Additionally, aligning the technology's purpose with customers' needs can contribute to trust. In order to utilize transaction services, consumers are typically required to provide personal information. It is crucial for these users to trust that mobile wallet services will not misuse their information. Therefore, mobile wallets must handle data security and privacy issues with the utmost care to maintain customer trust. Hence, the following hypothesis is proposed:

H10: TR has a significant and positive relationship with customers’ AT towards the adoption of mobile wallets in offline and online retail channels.

Attitude is a multi-dimensional construct encompassing a person's cognitive, affective, and behavioral responses towards products, services, or any other object of interest. It is an amalgamation of an individual's knowledge, experience, beliefs, and opinions that shape their perception of a particular entity. Attitude is not a fixed trait; various internal and external factors can influence it, such as personality, culture, social norms, and advertising messages (Chou et al., 2020; Hwang & Lyu, 2020).

Behavioral responses are the actions or intentions a person exhibits toward an object, such as purchasing, recommending, or avoiding it. Cognitive responses refer to a person's beliefs and knowledge about an object, including its attributes, benefits, and drawbacks (Kowalczuk et al., 2021). On the other hand, affective responses involve the emotional reactions and feelings that an individual associates with the object. These may include likes, dislikes, preferences, and physiological reactions such as arousal or relaxation (Kim et al., 2022).

Several studies have found that customer attitudes toward adopting new technologies can significantly and positively influence an individual's intention to use them. Park et al. (2019) suggested that attitude is critical in determining the intention to use mobile payment services. Similarly, Bailey et al. (2017) conducted recent research on mobile payment adoption by U.S. consumers and found that attitude had a significant and positive impact on behavioral intention.

Overall, the body of research on this topic highlights the importance of attitude in shaping individuals' adoption and use of new technologies. These findings affect businesses and marketers seeking to promote adopting new products and services. They suggest that addressing individuals' attitudes towards the technology can be critical in driving adoption and usage. Thus, the following hypothesis has been established:

H11: AT towards the adoption of mobile wallets in offline and online retail channels has a significant and positive relationship with the IU.

4. METHODOLOGY

A survey was conducted after reviewing relevant literature to understand and evaluate customer attitudes toward adopting mobile wallet technology in retail. The study consisted of 30 questions categorized into ten categories: transaction speed, optimism, discomfort, innovativeness, perceived ease of use, perceived enjoyment, perceived usefulness, trust, attitude, and intention to use. The survey identified a list of factors related to technology adoption.

The objective of the survey was to collect valuable insights regarding customers' perceptions of mobile wallet technology and identify the factors influencing their adoption and usage. It was conducted via a retail app accessible on customers' smartphones, and a reward of 5 Turkish Liras was provided to encourage participation. A pilot test involving 30 participants representing the target population was conducted to receive feedback on the questionnaire and evaluate the internal consistency of responses using Cronbach's alpha coefficient. Based on the feedback received, the survey was modified before being shared with the customers through the retailer's app. The survey was available for one month, and ultimately, 1728 customers who use mobile wallets regularly for in-store and online shopping completed the survey.

The questions were designed to rate the respondents' perception of the new technology adoption and their shopping intentions on a 7-point Likert scale, ranging from significantly below (1) to extremely above (7). In this thesis, the proposed model is tested by surveying 1728 customers, and the big scale of shopping data, including in-store and online customer transactions, is analyzed using the SEM technique via AMOS. Pearson’s Correlation Coefficient (r), Convergent Validity including Cronbach’s Alpha, Component Reliability, AVE, and Factor Loadings, and Discriminant Validity via Fornell–Larcker Criterion are employed for survey validation. Then, the hypothesis testing of the proposed model is evaluated with SPSS AMOS.

The descriptive statistic known as the Pearson correlation coefficient provides a summary of a dataset by describing the strength and direction of the linear association between two quantitative variables. The Pearson correlation coefficient (r) can also be viewed as a measure of the proximity of the observations to a line that best represents the relationship between the variables. Furthermore, the sign of the coefficient indicates whether the slope

of the line is positive or negative; if the slope is positive, r is also positive, and if the slope is negative, r is negative (Ahlgren et al., 2003).

A perfect linear relationship between two variables is indicated by a correlation coefficient (r) of either 1 or -1, in which case all the data points lie precisely on the line of best fit. The Pearson correlation coefficient (r) can be computed using the following formula:

$$r = \frac{\mathrm{n}\sum xy - (\sum x)(\sum y)}{\sqrt{[n\sum x^2 - (\sum x)^2][n\sum y^2 - (\sum y)^2]}} \quad (4.1)$$

The questionnaire was subjected to Confirmatory Factor Analysis (CFA) to evaluate the scales' reliability, convergent validity, and discriminant validity. For convergent validity, significant factor loadings should be greater than 0.7 at a p-value of less than 0.01. Additionally, all Average Variance Extracted (AVE) were above 0.5 (Bagozzi & Yi, 1988), and the Composite Reliability (CR) were above 0.7 (Gefen et al., 2000), while Cronbach Alpha (CA) values were above 0.6 (Hair et al., 2000). To test discriminant validity, the Fornell and Lacker criterion was employed, where the square root of the AVE was compared against the inter-correlations of the construct with other constructs in the model (Chin, 2010; Fornell & Larcker, 1981). The square root of the AVE exceeded correlations with other variables, thus indicating a satisfactory measurement model.

Cronbach's alpha coefficient is a statistical tool that assesses the internal consistency of a survey instrument. This coefficient yields a value between 0 and 1, where a higher value represents a stronger internal consistency. According to the recommendations proposed by Hair et al. (2000), a value below 0.6 in a survey like this would typically indicate unsatisfactory internal consistency. Cronbach's alpha formula is shown below:

$$\propto = \frac{N * \bar{c}}{\bar{v} + (N-1) * \bar{c}} \quad (4.2)$$

"N" refers to the total number of items being considered.

" $\bar{c}$ " represents the average covariance among items.

$\bar{v}$ is the mean item variance.

Composite reliability (CR) quantifies the degree of internal consistency within a set of

scale items, reflecting the extent of common variance among the observed variables that signify a latent construct. The equation to calculate CR, as proposed by Netemeyer et al. (2003), is presented below:

$$\text{CR}= \frac{(\sum_{i=1}^{p} \lambda_i)^2}{(\sum_{i=1}^{p} \lambda_i)^2 + \sum_{i}^{p} V(\delta)} \quad (4.3)$$

λ_i represents the standardized loading for the ith indicator.

V (δ_i) represents the variance of the error term for the ith indicator.

P is the number of indicators.

The Average Variance Extracted (AVE) quantifies the extent to which a construct accounts for the variance compared to the variance caused by measurement error (Fornell & Larcker, 1981). The following formula can be used to calculation of AVE:

$$AVE_x = \frac{\sum \lambda_{x.i}^2}{K_x} \quad (4.4)$$

$\lambda_{x.i}^2$ is equal to the square of the correlation coefficient between indicator x.i and the latent variable of X,

K_x represents the total quantity of indicators that are associated with X.

Furthermore, a test for discriminant validity was conducted. Initially, it was verified that the factor loadings of each item with respect to their corresponding latent variables were all higher than those of other constructs. Subsequently, the Fornell-Larcker criterion was employed to confirm discriminant validity. This criterion stipulates that no indicator variable, the squared root of each average variance extracted (AVE), should exhibit a stronger correlation with a different latent variable than its own (Fornell & Larcker, 1981).

Once validation and reliability tests were conducted, the survey questions aligned with the extended technology acceptance model factors. Structural Equation Modeling (SEM) is used to enhance the comprehension of how factors interrelate, test hypotheses, and elucidate technology-oriented customer shopping behaviors.

SEM is a robust statistical methodology that facilitates the examination of connections

between latent and observable variables. It enhances various multivariate methodologies, such as multiple regression analysis and factor analysis, by enabling the examination of interrelated relationships among variables simultaneously. By analyzing multiple equations within a single framework, SEM is a suitable statistical tool for evaluating complex models (Hair Jr. et al., 2014).

In the research of Joreskog & Bentler (1993), the importance of SEM was underscored, highlighting its distinct advantages compared to multiple regression analysis. Although similar to the latter method, SEM offers additional benefits. It can investigate nonlinear relationships and interactions among variables, assess the associations among independent variables, and quantify measurement errors and their correlations. Lastly, SEM can explore multiple latent variables measured by several indicators or reagents.

SEM is a statistical approach that tests hypotheses by examining the means, variances, and covariances of features within a specified model. Through this technique, researchers can analyze multiple dependent variables and assess one variable's direct and indirect impact on another (Koloor et al., 2015).

SEM offers a benefit in that it permits the inclusion of latent variables in the analysis. These conceptual constructs cannot be directly observed but can be measured through observable variables. Using latent variables can enhance the representation of theoretical concepts by employing multiple measures, thereby minimizing measurement error. This approach also aids in improving the estimation of the relationships between concepts by clarifying measurement errors in the constructs (Hair Jr. et al., 2014). This thesis hypothesizes ten latent variables to understand customer attitudes towards technology-driven products, including transaction speed, optimism, discomfort, innovativeness, perceived ease of use, perceived enjoyment, perceived usefulness, trust, attitude, and intention to use.

Various software programs are available for conducting SEM, such as EQS, LISREL, AMOS, Smart PLS, Mplus, and CALIS. This study utilized AMOS for the analysis as it offers a user-friendly graphical interface for all its functions, thereby eliminating the requirement for syntax commands or computer code (Hair Jr. et al., 2014).

Table 4.1 displays effective overall fit indices for the proposed SEM models to the data, which offer crucial insights into the model's appropriateness and compatibility with the

data. Such indices enable researchers to evaluate the accuracy of their hypotheses.

Table 4.1 SEM fit indices. Source: Bryne, 2001 & Koloor et al., 2015.

Abbreviation	Index Name	Critical Values
X^2	Chi-square	>5% Acceptable fit
GFI	Goodness of Fit Index	0=poor fit ,1=exact fit
AGFI	Modified Goodness of Fit Indices	-∞ = poor fit, 1=exact fit
CFI	Comparative Fit Index	0=poor fit 1=exact fit CFI>90% good fit
NFI	Normed Fit Index	0=poor fit ,1=exact fit NFI>90% good fit
TLI	Tucker Lewis Index	0=poor fit 1=exact fit
PNFI	Parsimony Normed Fit Index	>50% acceptable fit
IFI	Increasing Fit Index	0=poor fit 1=exact fit IFI>90% good fit
RMSEA	Root Mean Squared Error of Approximation	RMSEA <10% acceptable fit
CMIN/df	Chi Square/ Degree of Freedom	1<X^2/df<5 acceptable fit

The goodness of fit pertains to the level of correspondence between an estimated model and the observed data. This assessment is made by mathematically comparing the observed and estimated covariance matrices with a favorable outcome indicating that the model is an adequate fit.

In evaluating the disparities between the observed and estimated covariance matrices, The Chi-Square (X^2) serves as a critical metric. It is computed using the following formula (Hair Jr. et al., 2014):

$$\mathrm{X}^2 = (\mathrm{N}-1)(\mathrm{S}-\sum_{\mathrm{k}}) \tag{4.5}$$

The total sample size is denoted by N, while S and $\sum_k$ refer to the observed and estimated covariance matrices, respectively.

In statistical methods, the term "degrees of freedom" pertains to the mathematical information that can be utilized to estimate model parameters. The formula for determining the degrees of freedom in SEM is as follows (Hair Jr. et al., 2014):

$$df = \frac{1}{2}[(p)(p + 1)] - k \quad (4.6)$$

The variable "p" indicates the overall count of observed variables, while "k" denotes the estimated parameter numbers.

The Goodness of Fit Index (GFI) is a statistical measure that is relatively less sensitive to the sample size as it considers the N effect. It aims to assess the degree to which the estimated model fits the observed data. GFI can be calculated using the following formula (Hair Jr. et al., 2014):

$$\mathrm{GFI} = 1 - \frac{\mathrm{F_k}}{\mathrm{F_0}} \quad (4.7)$$

After SEM estimates using k degrees of freedom, F_k is the minimum fit function. F_0 refers to the fit function under the assumption that all parameters were zero and uncorrelated with each other.

The Adjusted Goodness of Fit Index (AGFI) is a measure that considers the model's complexity and adjusts for it, penalizing more complex models. This method does not have an associated statistical test. The Normed Fit Index (NFI) is the ratio of the difference between the X^2 value of the fitted model and the X^2 value of the null model. It provides a measure of the model's goodness of fit while considering the chance improvement in a fit that can be obtained by adding more parameters.

A more advanced version of NFI is the Comparative Fit Index (CFI), which provides an upgraded version of the model fit measure. A CFI value greater than 0.90 indicates that the model is a good fit. The CFI can be calculated using the following equation:

$$\mathrm{CFI} = 1 - \frac{(\mathrm{X_k^2} - \mathrm{df_k})}{(\mathrm{X_N^2} - \mathrm{df_N})} \quad (4.8)$$

PNFI and IFI are two other variants of NFI used in SEM. To obtain PNFI, NFI is multiplied by the parsimony ratio (PR) to adjust for model complexity. PR can be calculated using the following formula (Hair Jr. et al., 2014):

$$PR = \frac{df_k}{df_t} \tag{4.9}$$

A model's degrees of freedom represent the mathematical information used to estimate model parameters, expressed as a ratio of the total degrees of freedom.

The Tucker-Lewis Index (TLI) is an additional measure of fit that considers the differences in complexity between the specified and null models by comparing their normed chi-square values. It is familiar with the NFI. Therefore, TLI considers the degree of model complexity. The following formula can define TLI (Hair Jr. et al., 2014):

$$TLI = \frac{\left(\frac{X^2N}{df_N}\right) - \left(\frac{X_k^2}{df_k}\right)}{\left(\frac{X^2N}{df_N}\right) - 1} \tag{4.10}$$

“N” denotes the null model, whereas “k” denotes the specified model.

The Root Mean Squared Error of Approximation (RMSEA) is a measure of goodness of fit that adjusts for certain biases. A smaller RMSEA value indicates a better fit between the model and the data. RMSEA is calculated using the following formula (Hair Jr. et al., 2014):

$$RMSEA = \sqrt{\frac{X^2 - df_k}{(N-1)}} \tag{4.11}$$

5. DATA ANALYSIS AND RESULTS

A proposed model was developed using the TRAM model and context-specific constructs to determine customers' intention to use. A survey was conducted to comprehend and assess customers' inclination toward embracing mobile wallet technology in the retail industry. The survey was delivered to mobile wallet customers via the retailer's application. Using the retailer's data warehouse, customers who previously purchased with a mobile wallet were selected as participants in the survey. According to the customer information in the data set, the data ranges of the target population were determined. Hence, gender, age, education, time of use categories, and data ranges were checked. Table 5.1. shows the demographic measurement details of the survey participants.

Table 5.1 Demographic measurement details of survey participants.

Group	Number	Name
Gender	1	Female
	2	Male
Age	1	18-24
	2	25-30
	3	31-36
	4	37-45
	5	45+
Education	1	Highschool or less
	2	Undergraduate
	3	Graduate
Time of Use	1	Less than 1 year
	2	1-2 years
	3	2+ years

Firstly, a pilot test was carried out with 30 participants to represent the target population. Table 5.2. shows the demographic details of pilot test participants. The purpose of the pilot test was to obtain feedback on the questionnaire and to evaluate the internal consistency of responses using Cronbach's alpha coefficient. Table 5.3. shows the CA

results of 0.909, indicating the high internal consistency of the pilot test (Hair et al., 2000).

Table 5.2 Demographic details of the pilot test participants.

Age

Number	Frequency	Percent	Valid Percent	Cumulative Percent
1	5	16,7	16,7	16,7
2	4	13,3	13,3	30,0
3	10	33,3	33,3	63,3
4	9	30,0	30,0	93,3
5	2	6,7	6,7	100,0
Total	30	100,0	100,0	

Gender

Number	Frequency	Percent	Valid Percent	Cumulative Percent
1	13	43,3	43,3	43,3
2	17	56,7	56,7	100,0
Total	30	100,0	100,0	

Education

Number	Frequency	Percent	Valid Percent	Cumulative Percent
1	5	16,7	16,7	16,7
2	20	66,7	66,7	83,3
3	5	16,7	16,7	100,0
Total	30	100,0	100,0	

Time of Use

Number	Frequency	Percent	Valid Percent	Cumulative Percent
1	19	63,3	63,3	63,3
2	10	33,3	33,3	96,7
3	1	3,3	3,3	100,0
Total	30	100,0	100,0	

Table 5.3 Cronbach's Alpha Coefficient of the pilot test.

Cronbach's Alpha	N of Items
,909	30

Based on the feedback of the pilot test, the survey was revised before being distributed through the retailer's app. The survey was made available for one month with a number of 2200 participants. In the end, 1728 customers who use mobile wallets regularly for in-store and online shopping completed the survey. Table 5.4. shows the demographic details.

Table 5.4 Demographic details of the survey.

Age

Number	Frequency	Percent	Valid Percent	Cumulative Percent
1	201	11,6	11,6	11,6
2	232	13,5	13,5	25,1
3	606	35,1	35,1	60,2
4	513	29,7	29,7	89,9
5	175	10,1	10,1	100,0
Total	1727	100,0	100,0	

Gender

Number	Frequency	Percent	Valid Percent	Cumulative Percent
1	796	46,1	46,1	46,1
2	931	53,9	53,9	100,0
Total	1727	100,0	100,0	

Education

Number	Frequency	Percent	Valid Percent	Cumulative Percent
1	280	16,2	16,2	16,2
2	1193	69,1	69,1	85,3
3	254	14,7	14,7	100,0
Total	1727	100,0	100,0	

Table 5.4 (Continued) Demographic details of the survey.

Time of Use				
Number	Frequency	Percent	Valid Percent	Cumulative Percent
1	915	53,0	53,0	53,0
2	618	35,8	35,8	88,8
3	194	11,2	11,2	100,0
Total	1727	100,0	100,0	

Figure 5.1 illustrates the participant's gender number. There are 931 male participants, while 796 female answers the survey.

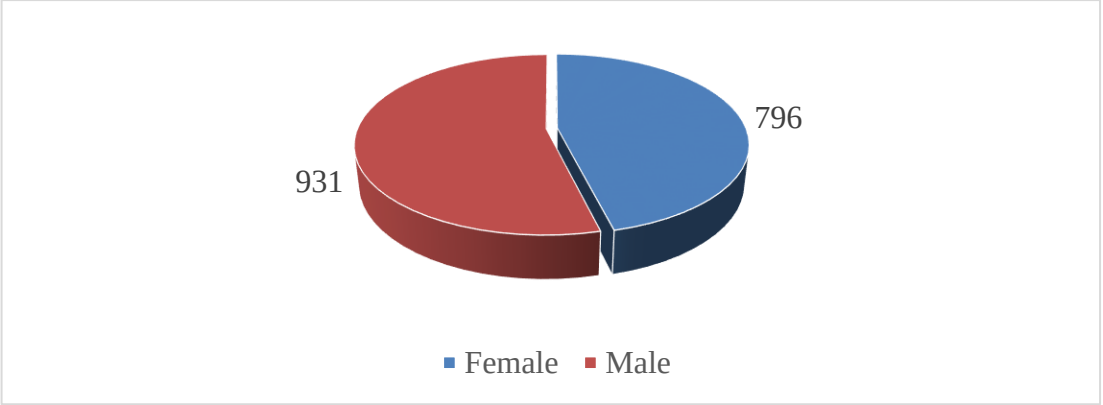


Figure 5.1 Number of the participants' genders.

The largest age group of the survey participants is the 31-36 age group, with 35.1%. The age ranges of the questionnaire are shown in Figure 5.2.

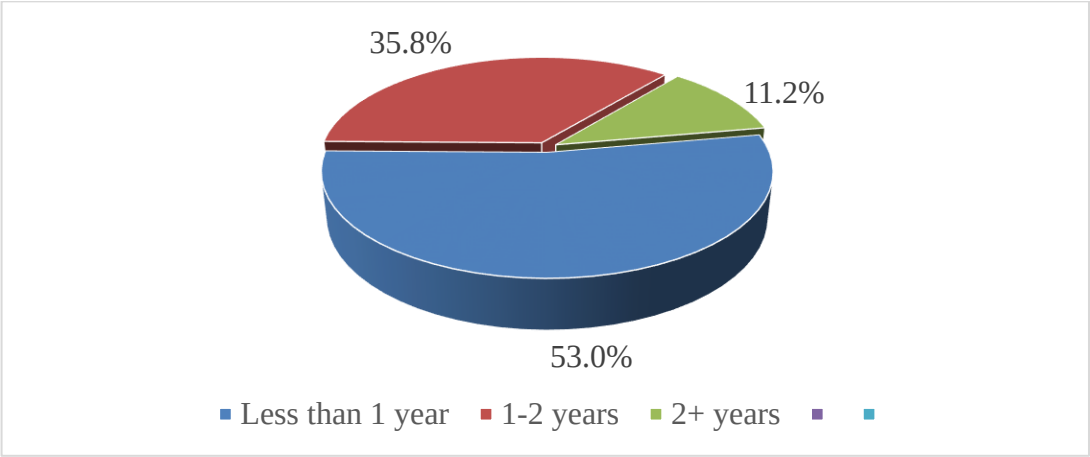


Figure 5.2 Rates of age groups.

When the educational status of the survey participants is examined, a not-surprising result is encountered. The number of those with a bachelor's degree in education is 1193, and the rate is 69.1%. The rate of graduate and higher users is 14.7%, and the rate of high school or less graduates is 16.2%. Mobile wallets, which are technology-oriented and especially appealing to new-generation customers, are preferred by young and well-educated users. Customer education rates are shown in Figure 5.3.

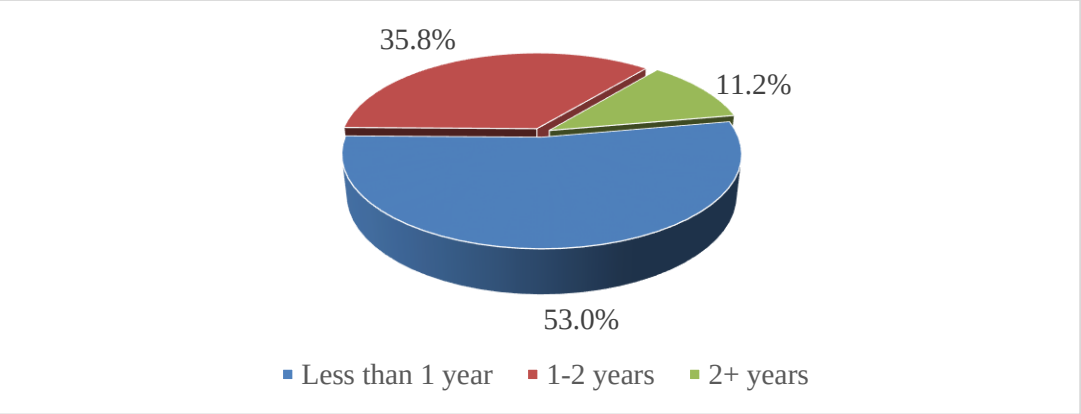


Figure 5.3 Customer education rates.

When the mobile wallet time of use rates are examined, it is observed that the majority of customers are 53% less than 1 year (Figure 5.4). With the effect of being a new product, the rate of 2+ year customers is the lowest, with 11.2%.

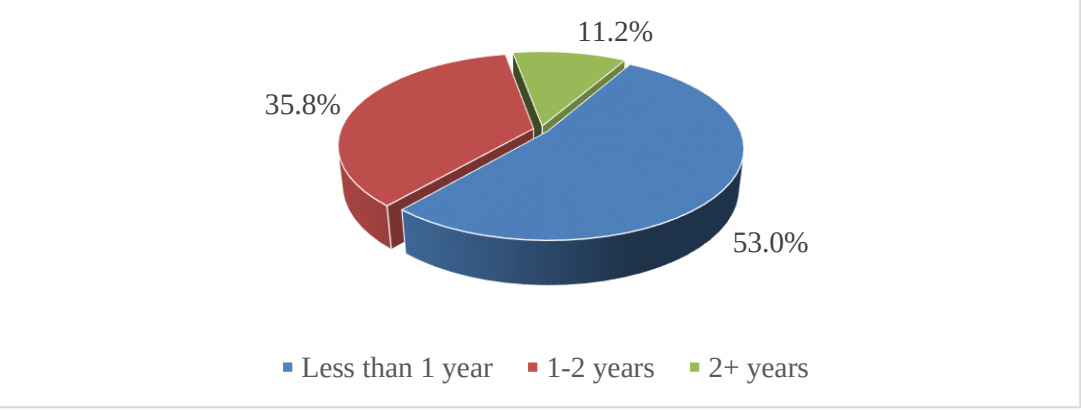


Figure 5.4 Time of use rates.

The mean of the answers to the latent variables' questions is shown in Figure 5.5. In Appendix, questions directed to survey participants can be accessed.

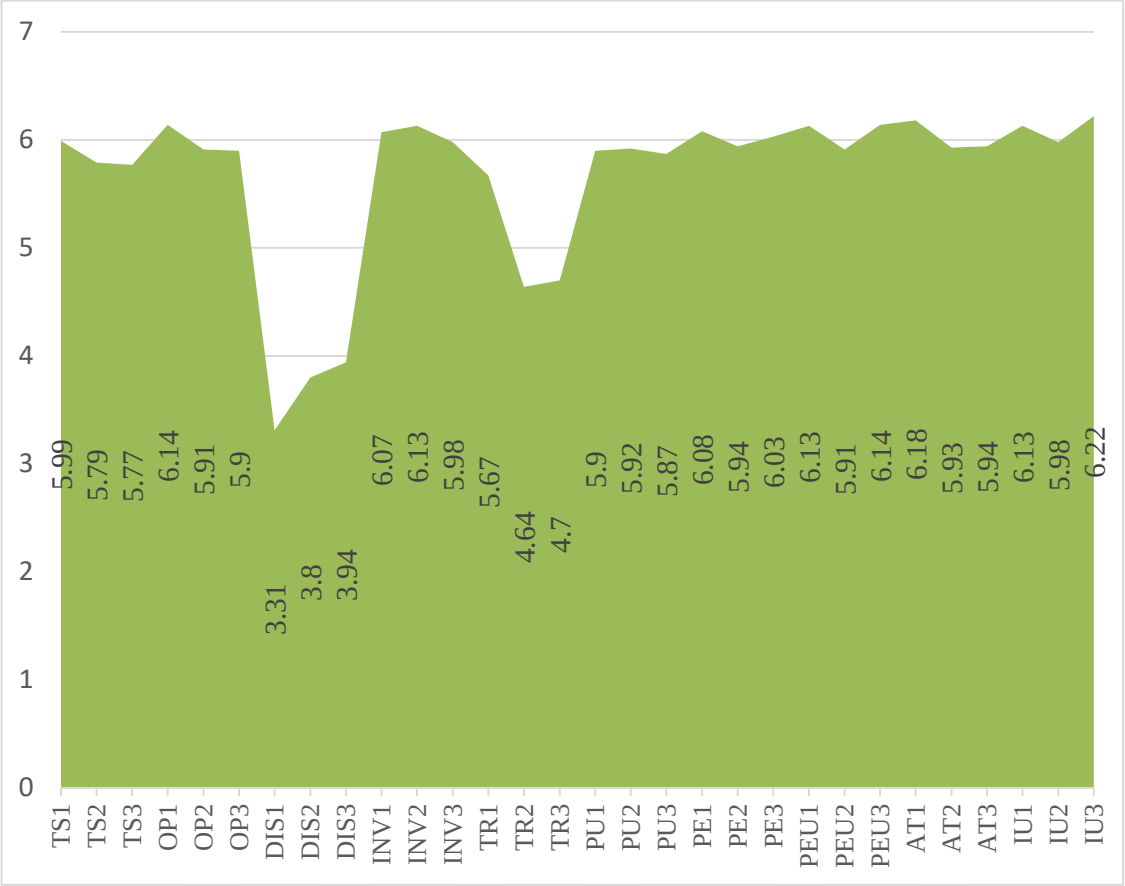


Figure 5.5 Graph of the mean of latent variables.

Reliability was tested before the hypothesis analysis. Cronbach's coefficients for all latent variables are shown in Table 5.5. According to the CA results, each of the factors is greater than 0.7, and the CA of the survey is 0.862. Therefore, high internal consistency of the survey was observed (Hair et al., 2000).

Table 5.5 Cronbach's Alpha Coefficient of survey factors.

Factors	Cronbach's Alpha
Transaction Speed	0.847
Optimism	0.838
Innovativeness	0.785
Discomfort	0.794
Trust	0.83
Perceived Ease of Use	0.761
Perceived Enjoyment	0.819

Table 5.5 (Continued) Cronbach's Alpha Coefficient of survey factors.

Factors	Cronbach's Alpha
Perceived Usefulness	0.812
Attitude	0.827
Intention to Use	0.858
All Variables	0.862

Pearson's correlation coefficients of latent variables were first measured with SPSS for convergent validity, and factor loadings were calculated to ensure robustness. According to Pearson's r, it was seen that there was a positive and 0.01 level significant relationship between the related latent variables (Table 5.6-5.15).

** The correlation is significant ($p < 0.01$ & 2-tailed) in the Tables 5.6-5.15.

Table 5.6 Pearson Correlations: Transaction Speed.

		TS1	TS2	TS3
TS1	Pearson Correlation	1.000	.717**	.618**
	Significance		.000	.000
	N	1727	1727	1727
TS2	Pearson Correlation	.717**	1.000	.611**
	Significance	.000		.000
	N	1727	1727	1727
TS3	Pearson Correlation	.618**	.611**	1.000
	Significance	.000	.000	
	N	1727	1727	1727

Table 5.7 Pearson Correlations: Optimism.

		OP1	OP2	OP3
OP1	Pearson Correlation	1.000	.683**	.625**
	Significance		.000	.000
	N	1727	1727	1727
OP2	Pearson Correlation	.683**	1.000	.592**
	Significance	.000		.000
	N	1727	1727	1727
OP3	Pearson Correlation	.625**	.592**	1.000
	Significance	.000	.000	
	N	1727	1727	1727

Table 5.8 Pearson Correlations: Discomfort.

		DIS1	DIS2	DIS3
DIS1	Pearson Correlation	1.000	.622**	.478**
	Significance		.000	.000
	N	1727	1727	1727
DIS2	Pearson Correlation	.622**	1.000	.546**
	Significance	.000		.000
	N	1727	1727	1727
DIS3	Pearson Correlation	.478**	.546**	1.000
	Significance	.000	.000	
	N	1727	1727	1727

Table 5.9 Pearson Correlations: Innovativeness.

		INV1	INV2	INV3
INV1	Pearson Correlation	1.000	.507**	.478**
	Significance		.000	.000
	N	1727	1727	1727
INV2	Pearson Correlation	.507**	1.000	.700**
	Significance	.000		.000
	N	1727	1727	1727
INV3	Pearson Correlation	.478**	.700**	1.000
	Significance	.000	.000	
	N	1727	1727	1727

Table 5.10 Pearson Correlations: Trust.

		TR1	TR2	TR3
TR1	Pearson Correlation	1.000	.655**	.470**
	Significance		.000	.000
	N	1727	1727	1727
TR2	Pearson Correlation	.655**	1.000	.728**
	Significance	.000		.000
	N	1727	1727	1727
TR3	Pearson Correlation	.470**	.728**	1.000
	Significance	.000	.000	
	N	1727	1727	1727

Table 5.11 Pearson Correlations: Perceived Usefulness.

		PU1	PU2	PU3
PU1	Pearson Correlation	1.000	.616**	.569**
	Significance		.000	.000
	N	1727	1727	1727
PU2	Pearson Correlation	.616**	1.000	.590**
	Significance	.000		.000
	N	1727	1727	1727
PU3	Pearson Correlation	.569**	.590**	1.000
	Significance	.000	.000	
	N	1727	1727	1727

Table 5.12 Pearson Correlations: Perceived Enjoyment.

		PE1	PE2	PE3
PE1	Pearson Correlation	1.000	.615**	.651**
	Significance		.000	.000
	N	1727	1727	1727
PE2	Pearson Correlation	.615**	1.000	.551**
	Significance	.000		.000
	N	1727	1727	1727
PE3	Pearson Correlation	.651**	.551**	1.000
	Significance	.000	.000	
	N	1727	1727	1727

Table 5.13 Pearson Correlations: Perceived Ease of Use.

		PEU1	PEU2	PEU3
PEU1	Pearson Correlation	1.000	.620**	.482**
	Significance		.000	.000
	N	1727	1727	1727
PEU2	Pearson Correlation	.620**	1.000	.439**
	Significance	.000		.000
	N	1727	1727	1727
PEU3	Pearson Correlation	.482**	.439**	1.000
	Significance	.000	.000	
	N	1727	1727	1727

Table 5.14 Pearson Correlations: Attitude.

		AT1	AT2	AT3
AT1	Pearson Correlation	1.000	.706**	.591**
	Significance		.000	.000
	N	1727	1727	1727
AT2	Pearson Correlation	.706**	1.000	.555**
	Significance	.000		.000
	N	1727	1727	1727
AT3	Pearson Correlation	.591**	.555**	1.000
	Significance	.000	.000	
	N	1727	1727	1727

Table 5.15 Pearson Correlations: Intention to Use.

		IU1	IU2	IU3
IU1	Pearson Correlation	1.000	.656**	.672**
	Significance		.000	.000
	N	1727	1727	1727
IU2	Pearson Correlation	.656**	1.000	.676**
	Significance	.000		.000
	N	1727	1727	1727
IU3	Pearson Correlation	.672**	.676**	1.000
	Significance	.000	.000	
	N	1727	1727	1727

Factor loadings are computed using principal component analysis (PCA) following Pearson's correlation for each latent variable to ensure the factors' robustness. For rotation, the Varimax method with Kaiser Normalization is preferred. This is because Varimax Rotation, also referred to as Kaiser-Varimax rotation, seeks to maximize the total variance of the squared loadings, where loadings denote the correlations between factors and variables. This approach generally yields high factor loadings for a small subset of variables and low factor loadings for the remaining ones.

Table 5.16 demonstrates the factor loadings. Items with loadings lower than 0.7 should be discarded for reliability (Hair et al., 2010). Accordingly, INV1 and PEU3 were discarded, and PCA was implemented again.

Table 5.16 Factor loadings.

	Component									
	1	2	3	4	5	6	7	8	9	10
TS2	,871									
TS1	,859									
TS3	,799									
OP1		,836								
OP3		,809								
OP2		,809								
IU3			,826							
IU2			,820							
IU1			,760							
TR2				,925						
TR3				,853						
TR1				,780						
AT1					,831					
AT2					,806					
AT3					,737					
PE1						,836				
PE3						,799				
PE2						,790				
PU2							,833			
PU1							,807			
PU3							,778			
INV3								,852		
INV2								,841		
INV1								,685		
DIS2									,866	
DIS1									,824	
DIS3									,799	
PEU2										,830
PEU1										,803
PEU3										,693

Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization (a. Rotation converged in 6 iterations).

Based on the PCA results, INV1 and PEU3 were discarded. Then the analysis was conducted without these two items. Table 5.17 shows the factor loadings 2nd iteration. According to the results, all items with loadings are higher than 0.7. Therefore, the accuracy of model fit is provided.

Table 5.17 Factor loadings 2nd iteration.

Factors	λ (2nd Iteration)
TS1	0.862
TS2	0.873
TS3	0.802
OP1	0.84
OP2	0.811
OP3	0.812
IU1	0.765
IU2	0.823
IU3	0.831
TR1	0.778
TR2	0.927
TR3	0.856
AT1	0.835
AT2	0.808
AT3	0.745
PE1	0.839
PE2	0.796
PE3	0.801
PU1	0.811
PU2	0.836
PU3	0.78
INV1	0.859
INV2	0.884
DIS1	0.823
DIS2	0.867
DIS3	0.802
PEU1	0.825
PEU2	0.876

After ensuring the accuracy of factor loadings, further analysis was applied for convergent validity in the model. Therefore, the CR and AVE tests were conducted (Table 5.18). Accordingly, CR values greater than 0.7 range from 0.839 to 0.891, reflecting the validity of all measurements. Finally, the AVE for each factor is greater than 0.5 (ranging from 0.635 to 0.759), demonstrating the accuracy of the factors.

Table 5.18 CR and AVE results of factors.

Factors	CR	AVE
TS	0.883	0.716
OP	0.861	0.674
DIS	0.87	0.691
INV	0.863	0.759
TR	0.891	0.732
PU	0.851	0.655
PE	0.853	0.659
PEU	0.84	0.724
AT	0.839	0.635
IU	0.848	0.651

Finally, the Fornell-Larcker criterion was used to ensure discriminant validity. According to the criterion, no indicator variable should have a higher correlation with another latent variable than with its own latent variable. Table 5.19 shows the results.

Table 5.19 Interconstruct correlations.

	TS	OP	DIS	INV	TR	PU	PE	PEU	AT	IU
TS	**0.846**									
OP	,305**	**0.821**								
DIS	-,083**	-,057*	**0.831**							
INV	,243**	,275**	-,194**	**0.872**						
TR	,126**	,161**	-.024	,186**	**0.856**					
PU	,272**	,305**	-,128**	,290**	,127**	**0.809**				
PE	,254**	,279**	-,116**	,260**	,141**	,351**	**0.812**			
PEU	,257**	,234**	-,078**	,238**	,124**	,273**	,342**	**0.851**		
AT	,272**	,372**	-,107**	,269**	,153**	,363**	,365**	,315**	**0.797**	
IU	,249**	,430**	-,078**	,273**	,127**	,329**	,383**	,341**	,520**	**0.807**

Note: The green highlighted bold values are the squared root of AVE.

A structural model was constructed using SPSS AMOS and assessed using maximum likelihood estimation to examine the proposed hypotheses. The aim was to evaluate the connections among the theoretical constructs within the model. SPSS AMOS was selected for this analysis due to its user-friendly interface and ability to test relationships between observed and latent variables, enabling rapid hypothesis testing and confirmation of relationships. After conducting reliability and CFA tests, the path analysis is employed

for the hypothesis testing. The path diagram of the proposed model in AMOS is presented in Figure 5.6.

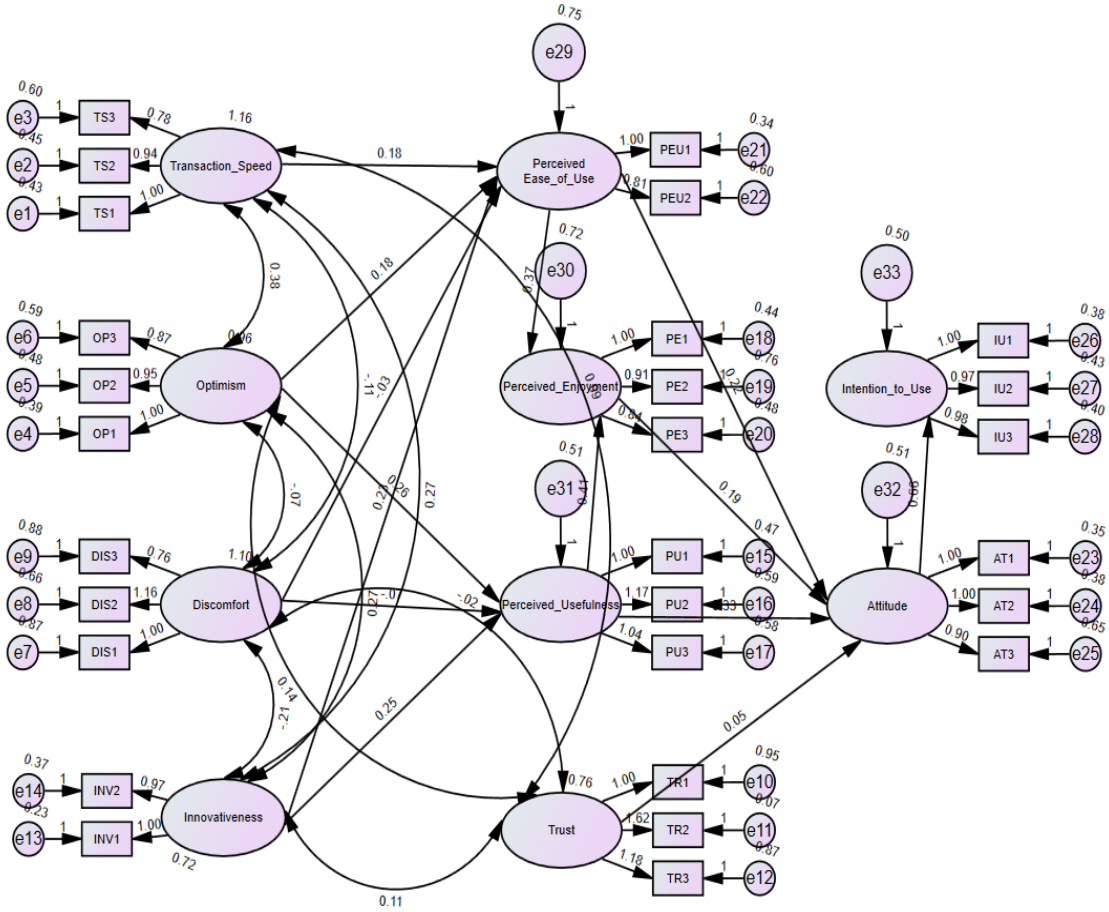


Figure 5.6 Path analysis of the proposed model in AMOS.

Table 5.20 displays the outcomes of the path analysis conducted using SPSS AMOS. The findings indicate that out of the 14 hypotheses formulated in the proposed model, 13 received significant support. The only exception was the hypothesis suggesting a negative and significant relationship between discomfort and perceived ease of use, which was found to be statistically insignificant.

Furthermore, the results revealed strong support for the majority of the hypotheses, indicating a robust relationship between the variables in the proposed model. Notably, the insignificant impact of discomfort on the perceived ease of use hypothesis may warrant further investigation to explore potential underlying factors or alternative explanations for this unexpected result.

Table 5.20 Summary of hypotheses testing results.

Paths			Estimate	S.E.	t-Value	P-Label	Supported
TS	-->	PEU	0.185	0.027	6.75	***	Yes
OP	-->	PEU	0.183	0.031	5.933	***	Yes
OP	-->	PU	0.262	0.025	10.527	***	Yes
DIS	-->	PEU	-0.026	0.027	-0.965	0.334	No
DIS	-->	PU	-0.071	0.022	-3.238	0.001	Yes
INV	-->	PEU	0.228	0.036	6.277	***	Yes
INV	-->	PU	0.247	0.030	8.222	***	Yes
PEU	-->	PE	0.370	0.032	11.728	***	Yes
PU	-->	PE	0.408	0.035	11.746	***	Yes
PU	-->	AT	0.326	0.031	10.361	***	Yes
PE	-->	AT	0.186	0.028	6.681	***	Yes
PEU	-->	AT	0.220	0.028	7.907	***	Yes
TR	-->	AT	0.055	0.023	2.349	0.019	Yes
AT	-->	IU	0.663	0.029	22.632	***	Yes

The results of the path analysis for the standardized model are displayed in Table 5.20 and Figure 5.7. These findings reveal the path coefficients, which signify the strength and direction of the relationships between the variables. It is noteworthy that a significant number of the hypothesized paths among the latent variables show statistical significance. Accordingly, transaction speed significantly affects perceived ease of use ($\beta = 0.185$, $p < 0.001$), which supports H1. Optimism has a significant positive impact on perceived ease of use ($\beta = 0.183$, $p < 0.001$) and perceived usefulness ($\beta = 0.262$, $p < 0.001$), which support H2a and H2b. On the other hand, discomfort does not significantly affect perceived ease of use ($\beta = -0.026$, $p < 0.05$); thus, H3a is rejected. In contrast, discomfort negatively and significantly affects perceived usefulness ($\beta = -0.071$, $p < 0.01$). Therefore, H3b is supported. Additionally, innovativeness exhibits a significantly positive influence on perceived ease of use ($\beta = 0.228$, $p < 0.001$) and perceived usefulness ($\beta = 0.247$, $p < 0.001$), which support H4a and H4b.

Furthermore, perceived ease of use ($\beta = 0.370$, $p < 0.001$) and perceived usefulness ($\beta = 0.408$, $p < 0.001$) are found to have a positively significant influence on perceived

enjoyment, which supports H5 and H6. Also, path analysis results showed that perceived ease of use ($\beta = 0.220$, $p < 0.001$), perceived enjoyment ($\beta = 0.186$, $p < 0.001$), perceived usefulness ($\beta = 0.326$, $p < 0.001$), and trust ($\beta = 0.055$, $p < 0.05$) positively significant effect on attitude. Therefore, H7, H8, H9, and H10 is supported. Finally, the results revealed that attitude has a positively significant impact on intention to use ($\beta = 0.663$, $p < 0.001$), which supports H11.

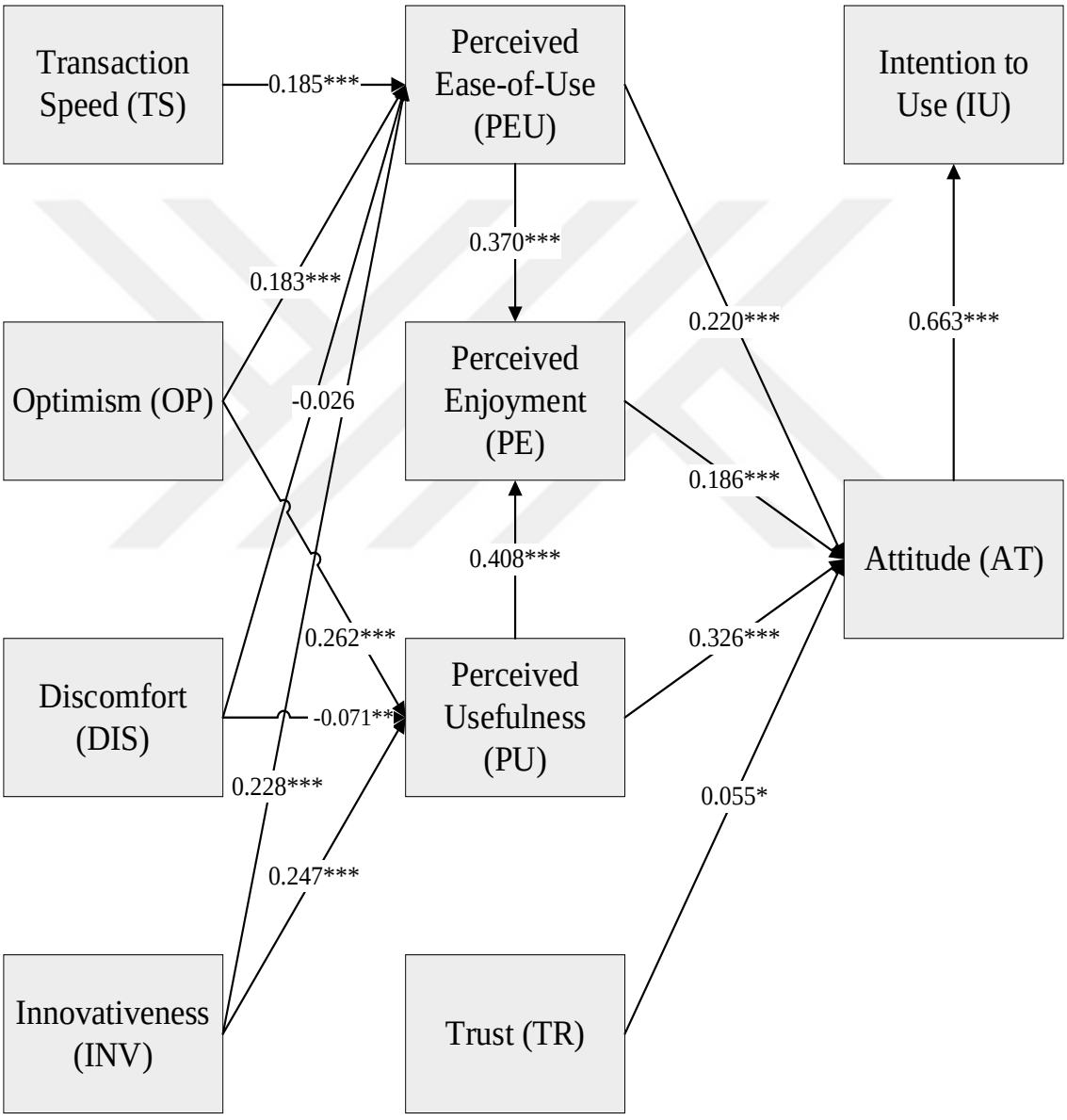


Figure 5.7 Standardized model with path coefficients.

Table 5.21 shows the model fit summary of the analysis. According to the results, the model is suitable for the SEM fit indices (Koloor et al., 2015 & Bryne 2001). As it is

shown in Table 5.21, CMIN/df is 3.45, which is suitable with the reference interval (1<X^2/df<5 acceptable fit). Additionally, GFI is 0.956 (1= exact fit), NFI is 0.948 (CFI > 90% good fit), CFI is 0.963 (CFI > 90% good fit), and RMSEA is 3.8% (RMSEA < 10% acceptable fit).

Table 5.21 Model fit summary.

CMIN					
Model	**NPAR**	**CMIN**	**DF**	**P**	**CMIN/df**
Default model	80	1124.766	326	0.000	3.450
Saturated model	406	0.000	0		
Independence model	28	21716.06	378	0.000	57.450
RMR, GFI					
Model	**RMR**	**GFI**	**AGFI**	**PGFI**	
Default model	0.087	0.956	0.946	0.768	
Saturated model	0.000	1.000			
Independence model	0.335	0.365	0.318	0.340	
Baseline Comparison					
Model	**NFI**	**RFI**	**IFI**	**TLI**	**CFI**
	Delta1	**rho1**	**Delta2**	**rho2**	
Default model	0.948	0.940	0.963	0.957	0.963
Saturated model	1.000		1.000		1.000
Independence model	0.000	0.000	0.000	0.000	0.000
RMSEA					
Model	**RMSEA**	**LO 90**	**HI 90**	**PCLOSE**	
Default model	0.038	0.035	0.040	1.000	
Independence model	0.181	0.179	0.183	0.000	

6. DISCUSSION

This thesis focuses on exploring customer attitudes towards technology-driven products. In the literature, while the mobile wallet product has been examined in depth, smart retail technologies have also been extensively analyzed. The selected articles from the last decade have provided a detailed understanding of the subject matter, allowing for a comprehensive analysis and evaluation of the mobile wallet's impact on customer perceptions and behaviors. Various models in the literature for technology acceptance have been scanned for this purpose. The literature has shown that although mobile wallets are a new technology, they increasingly attract customers' attention. A TRAM-based proposed model was created in order to understand utilitarian and hedonic customer expectations and to give advice to merchants with shopping purchase intentions. Transaction speed and trust factors were added to the model to accurately describe shopping habits and customer experience.

For this study, a thorough literature review was conducted to explore various technology acceptance models. It has been observed that mobile wallets, although it is a relatively new technology, have been gaining significant attention from customers. In light of this finding, a proposed model based on Technology Readiness Acceptance Model (TRAM) was developed to delve into customers' utilitarian and hedonic expectations and provide valuable insights to merchants regarding shopping purchase intentions.

In addressing the research gap surrounding customer attitudes toward mobile wallets and their impact on shopping behaviors, this study introduces an original model that extends the existing literature. By incorporating transaction speed and trust factors, the proposed model aims to comprehensively understand customers' shopping habits and overall experience when utilizing mobile wallets.

The inclusion of transaction speed as a factor in the model recognizes its significance in influencing customer perceptions and satisfaction. Previous research has highlighted the importance of quick and efficient transactions, as they contribute to a seamless and convenient shopping experience. By incorporating transaction speed into the model, merchants can gain insights into how this factor influences customers' adoption and usage of mobile wallets.

Similarly, trust plays a vital role in shaping customer behavior and decision-making processes. Trust is a crucial factor that affects customers' willingness to adopt and utilize mobile wallet services. By incorporating trust into the proposed model, merchants can better understand its influence on customers' attitudes and intentions. This understanding can guide merchants in building trust-enhancing strategies and fostering long-term customer relationships.

By introducing these additional factors and building upon existing theories, the proposed model fills a research gap by providing a more comprehensive framework for understanding customer expectations and preferences in the context of mobile wallet usage. This model serves as a valuable tool for merchants, enabling them to make data-driven decisions and tailor their strategies to meet customers' needs better and enhance their shopping experiences.

The results of the hypothesis testing reveal that thirteen of the fourteen hypotheses are confirmed to be significant. Accordingly, transaction speed positively affects perceived ease of use. Optimism and innovativeness are positively related to perceived ease of use and perceived usefulness. Discomfort negatively affects perceived usefulness. On the other hand, test results show that discomfort has no significant effect on perceived ease of use.

Furthermore, perceived usefulness and perceived ease of use have a positively significant influence on perceived enjoyment. Also, perceived ease of use, perceived enjoyment, perceived usefulness, and trust are positively related to attitude. Lastly, attitude significantly and positively affects the usage intention.

This study's findings reveal the connections among different factors in the context of technology-driven products. The results indicate that perceived ease of use, perceived enjoyment, perceived usefulness, and trust significantly positively influence customer attitudes. Furthermore, customer attitude positively influences their intention to use such products.

These results imply that when customers perceive technology-driven products, whether in-store or online, as easy to use, they enhance their utilitarian benefits, such as improved shopping effectiveness and a streamlined purchase process. This finding is supported by the positive relationships observed between transaction speed, customer innovativeness,

optimism, and perceived ease of use. These factors contribute to customers' overall positive experience and increase their willingness to engage with smart products.

Moreover, the significant positive effect of perceived usefulness on customer attitudes suggests that if customers believe that technology-driven products can enhance their purchase process and provide a more efficient shopping experience, they are more inclined to adopt and use these products. The model further reveals that optimism and customer innovativeness positively contribute to the perceived usefulness, while discomfort exerts a significantly negative influence.

These findings highlight the importance of perceived ease of use and perceived usefulness as drivers of customer attitudes toward technology-driven products. By designing and implementing products that are easy to use and deliver tangible benefits to customers, retailers can effectively increase customer acceptance and adoption of smart products. Furthermore, considering factors such as transaction speed, customer innovativeness, optimism, and minimizing discomfort can further enhance customers' perceived ease of use and perceived usefulness.

In addition to perceived usefulness and perceived ease of use, perceived enjoyment assumes a particularly significant role in augmenting the hedonic benefits associated with technology-driven products, ultimately contributing to customer satisfaction and shopping pleasure. While the functionality of technology-driven products attracts customers, the fun and enjoyment derived from using technology predominantly influence customer attitudes and intentions to use such products. Consequently, when customers perceive their in-store or online purchasing experience as satisfactory and pleasurable, their inclination to engage in shopping activities is significantly heightened.

The concept of perceived enjoyment holds significant importance in technology-driven products. When customers find joy, excitement, and entertainment in utilizing these products, it fosters positive emotions and enhances their overall shopping experience. This emotional connection with technology-driven products contributes to the formation of favorable attitudes, ultimately influencing customers' intentions to continue using them.

The positive relationship between perceived enjoyment and hedonic benefits underscores the role of fun and pleasure in driving customer satisfaction and shopping pleasure.

Customers who enjoy using technology-driven products experience a heightened sense of satisfaction and fulfillment during the purchasing process. This positive emotional state further motivates them to engage in future shopping activities.

Briefly, the perceived enjoyment associated with technology-driven products acts as a catalyst, amplifying hedonic benefits such as satisfaction and shopping pleasure. The attractiveness of the product's functionality, combined with the fun and enjoyment derived from its use, significantly impacts customer attitudes and intentions to use. Therefore, when customers perceive their in-store or online purchasing process as satisfactory and enjoyable, their inclination to engage in shopping activities is greatly heightened.

In the context of managerial and practice implications, by delivering enjoyable experiences, ensuring ease of use, providing trustful processes, and highlighting the practical benefits, retailers can foster customer loyalty, extend customer relationships, and reduce churn, resulting in long-term success for technology-driven products. To enhance customer lifetime value, retailers should prioritize creating technology-driven products that offer functional benefits and provide customers with enjoyment and pleasure. Companies can cultivate a deeper emotional connection with customers by designing products that evoke positive emotions and deliver engaging experiences. This connection increases customer satisfaction and loyalty, leading to prolonged engagement and repeated purchases, ultimately enhancing customer lifetime value.

Technology-driven, user-friendly, smart products can enhance the overall customer experience, reducing frustration and increasing satisfaction. Simultaneously, emphasizing the factors of perceived ease of use and perceived usefulness is crucial in preventing churn. Likewise, emphasizing the practical benefits and value these products bring to customers' shopping experiences can reinforce their commitment and deter them from seeking alternatives.

Regularly incorporating features that enhance perceived enjoyment, ensuring ease of use, and demonstrating the usefulness of their products can create a positive feedback loop. This feedback loop fosters customer satisfaction, increases usage and engagement, and minimizes churn. By continuously striving to improve and innovate in these areas, businesses can stay ahead of competitors and maintain customer loyalty.

The findings of this study offer valuable insights for retailers and service designers of technology-driven products, guiding in understanding customers' utilitarian and hedonic motivations. The results highlight the significant impact of perceived ease of use and perceived usefulness on enhancing both perceived enjoyment and customer attitude. This situation emphasizes the importance for retailers and service providers to prioritize improving technology-driven products' ease of use and usefulness. Factors such as transaction speed, customer innovativeness, optimism, and reducing discomfort should be carefully evaluated and addressed to optimize the user experience.

Furthermore, the study reveals the crucial role of perceived enjoyment in shaping customer attitudes. Customers seek utilitarian benefits and expect a joyful shopping experience when using technology-driven products. Therefore, retailers are strongly recommended to allocate efforts towards enhancing the overall pleasant shopping experience in addition to focusing on utilitarian aspects.

Additionally, the significantly positive influence of trust on customer attitude underscores the importance of incorporating robust security and privacy features into technology-driven products. This instills confidence in customers and assures them of the trustworthiness of using these products.

In conclusion, the findings emphasize the need for retailers and service designers to prioritize improving the ease of use, usefulness, and perceived enjoyment of technology-driven products. Additionally, building trust through enhanced security and privacy features is crucial. By addressing these aspects, retailers can enhance customer attitudes and satisfaction and ultimately drive success in the competitive market of technology-driven products.

7. CONCLUSION

In today's rapidly evolving world, characterized by constant technological advancements and innovation, it has become exceedingly crucial for businesses to comprehend and cater to the needs of technology-oriented customers. Companies are expected to accurately identify these customers and optimize their service designs to provide them with a seamless technological innovation experience.

The primary focus of this thesis revolves around investigating customer attitudes towards technology-driven products. To achieve this objective, extensive analysis has been conducted on one of the prominent smart retail technologies, namely Fintech, within the existing literature. Within the realm of Fintech, particular attention has been given to examining the mobile wallet product in great depth. By delving into selected articles from the past decade, a comprehensive understanding of the subject matter has been attained, facilitating a thorough analysis and evaluation of the impact of mobile wallets on customer perceptions and behaviors.

The literature review has revealed that although mobile wallets represent a relatively new technology, they have been progressively capturing customers' attention. In order to address this phenomenon, various technology acceptance models have been scrutinized within the literature. As a result, a proposed model based on Technology Readiness and Acceptance Model (TRAM) has been developed. This model aims to comprehend both the utilitarian and hedonic customer expectations associated with technology-driven products, specifically focusing on providing guidance to merchants regarding shopping purchase intentions.

To accurately depict customers' shopping habits and overall experience, the proposed model incorporates additional factors such as transaction speed and trust. These factors have been identified as critical elements in accurately describing customer behavior and shaping their perception of technology-driven products. By incorporating these factors into the model, a more comprehensive view of customer expectations and preferences is achieved, empowering merchants to make informed decisions and tailor their strategies accordingly.

Through this research, a deeper understanding of customer attitudes towards

technology-driven products, with a specific emphasis on the mobile wallet, has been obtained. The analysis of various models and the development of a proposed TRAM-based model contribute to bridging the existing research gap and providing valuable insights for businesses operating in the realm of smart retail technologies.

The findings of the hypothesis testing in this study shed light on the crucial roles played by utilitarian motivations arising from perceived ease of use and perceived usefulness, as well as hedonic motivations stemming from perceived enjoyment. Notably, the study uncovers that transaction speed enhances perceived ease of use. Optimism, innovativeness, and discomfort also emerge as significant factors influencing both perceived ease of use and perceived usefulness. Furthermore, this thesis highlights the significant positive influence of trust on customer attitude and intention to use technology-driven products.

These findings carry important implications for future research and offer specific recommendations for retailers and service providers. Understanding the impact of utilitarian and hedonic motivations can guide future studies in exploring customer attitudes towards technology-driven products more comprehensively. Additionally, recognizing the positive influence of trust on customer attitude emphasizes the need for retailers and service providers to prioritize building secure and reliable technology-driven solutions.

The observed relationship between transaction speed and perceived ease of use underscores the importance of optimizing product performance and efficiency. Furthermore, the significant impact of factors such as optimism, innovativeness, and discomfort on perceived ease of use and perceived usefulness signifies the relevance of considering these aspects when designing and implementing technology-driven products.

Overall, these research findings contribute valuable insights that can shape future studies in the field. Moreover, the recommendations offer actionable suggestions for retailers and service providers to enhance their understanding of customer attitudes and optimize their strategies accordingly.

This thesis recognizes the presence of certain limitations that warrant acknowledgment. Firstly, the study was conducted in Turkey, and cultural variations

may influence consumer behaviors and attitudes toward new technologies. Therefore, future research is recommended to validate the findings in different countries.

Secondly, although the sample size met the required criteria for analysis, results may vary among different age groups, education, socioeconomic statuses, genders, and frequency of technology usage among participants. Conducting comparative analyses with external factors in future studies would be beneficial.

Lastly, the research employed a TRAM-based proposed model for analyzing customer attitudes. However, alternative models incorporating different factors could be explored to analyze customer attitudes comprehensively.

REFERENCES

Abbasi, G. A., Sandran, T., Ganesan, Y., & Iranmanesh, M. (2022). Go cashless! Determinants of continuance intention to use E-wallet apps: A hybrid approach using PLS-SEM and fsQCA. *Technology in Society*, 68, 101937.

Accenture. (2016). *Winning Experiences in the New Digital Landscape: A Global Consumer Study*. Retrieved from https://www.accenture.com/_acnmedia/PDF-17/Accenture-Winning-Experiences-in-the-New-Digital-Landscape.pdf

Adesina, Y., Gupta, R., & Singh, S. (2020). The challenges of fintech and the importance of regulatory technology (RegTech). *Journal of Financial Crime*, 27(1), 56-67.

Adjei, J. K., Odei-Appiah, S., & Tobbin, P. E. (2020). Explaining the determinants of continual use of mobile financial services. *Digital Policy, Regulation and Governance*, 22(1), 15-31.

Agarwal, R., & Prasad, J. (1997). The role of innovation characteristics and perceived voluntariness in the acceptance of information technologies. *Decision Sciences*, 28(3), 557-582.

Agarwal, R., & Prasad, J. (1998). A conceptual and operational definition of personal innovativeness in the domain of information technology. *Information Systems Research*, 9(2), 204-215.

Agarwal, S., Skiba, P. M., & Tobacman, J. (2018). Payday loans and credit cards: New liquidity and credit scoring puzzles? *Journal of Money, Credit and Banking*, 50(7), 1489-1527.

Aheleroff, S., Xu, X., Lu, Y., Aristizabal, M., Velásquez, J. P., Joa, B., & Valencia, Y. (2020). IoT-enabled smart appliances under industry 4.0: A case study. *Advanced engineering informatics*, 43, 101043.

Ahlgren, P., Jarneving, B., & Rousseau, R. (2003). Requirements for a cocitation similarity measure, with special reference to Pearson's correlation coefficient. *Journal of the American Society for Information Science and Technology*, 54(6), 550-560.

Aji, H. M., & Adawiyah, W. R. (2021). How e-wallets encourage excessive spending behavior among young adult consumers? *Journal of Asia Business Studies.*

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, 50(2), 179-211.

Ajzen, I., & Fishbein, M. (1980). Understanding attitudes and predicting social behavior. Englewood Cliffs, NJ: Prentice-Hall.

Akanfe, O., Valecha, R., & Rao, H. R. (2020). Assessing country-level privacy risk for digital payment systems. *Computers & Security,* 99, 102065.

Akanfe, O., Valecha, R., & Rao, H. R. (2020). Design of a Compliance Index for Privacy Policies: A Study of Mobile Wallet and Remittance Services. *IEEE Transactions on Engineering Management.*

Akanfe, O., Valecha, R., & Rao, H. R. (2020). Design of an inclusive financial privacy index (INF-PIE): a financial privacy and digital financial inclusion perspective. *ACM Transactions on Management Information Systems (TMIS),* 12(1), 1-21.

Al-Badi, A. H., Govindaluri, S. M., Sharma, S. K., & Khan, A. I. (2022). Global and local perspective on the usage of mobile wallet. *International Journal of Business Information Systems,* 39(4), 550-568.

Al-Gahtani, S. S. (2017). Empirical investigation of e-learning acceptance and assimilation: A structural equation model. *Applied Computing and Informatics,* 13(1), 27-50.

Al-Qudah, A. A., Al-Okaily, M., Alqudah, G., & Ghazlat, A. (2022). Mobile payment adoption in the time of the COVID-19 pandemic. *Electronic Commerce Research,* 1-25.

Alaeddin, O., Rana, A., Zainudin, Z., & Kamarudin, F. (2018). From physical to digital: Investigating consumer behaviour of switching to mobile wallet. *Polish Journal of Management Studies,* 17(2), 18-30.

Alam, M. M., Awawdeh, A. E., & Muhamad, A. I. B. (2021). Using e-wallet for business process development: challenges and prospects in Malaysia. *Business Process Management Journal.* Advance online publication. doi:10.1108/BPMJ-05-2021-0251.

Alalwan, A. A., Baabdullah, A. M., Rana, N. P., & Tamilmani, K. (2018). Factors influencing the adoption of mobile shopping applications: A UTAUT2-based study. *Journal of Retailing and Consumer Services,* 44, 225-235.

Alalwan, A. A., Dwivedi, Y. K., & Rana, N. P. (2017). Factors influencing adoption of mobile banking by Jordanian bank customers: Extending UTAUT2 with trust.

International Journal of Information Management, 37(3), 99-110.

Alalwan, A. A., Dwivedi, Y. K., & Rana, N. P. (2020). Factors influencing consumer adoption of self-service technologies in the retail context: The moderating role of trust. *Journal of Retailing and Consumer Services,* 52, 101934.

Alalwan, A. A., Rana, N. P., Dwivedi, Y. K., & Algharabat, R. (2017). The Impact of Social Media on Consumer Buying Intention. *Journal of Marketing Management,* 33(1-2), 1-17.

Alexander, B., & Kent, A. (2020). Change in technology-enabled omnichannel customer experiences in-store. *Journal of Retailing and Consumer Services,* 102338.

Alswaigh, N. Y., & Aloud, M. E. (2021). Factors Affecting User Adoption of E-Payment Services Available in Mobile Wallets in Saudi Arabia. *International Journal of Computer Science & Network Security,* 21(6), 222-230.

Amoroso, D., & Ackaradejruangsri, P. (2017). How consumer attitudes improve repurchase intention. *International Journal of E-Services and Mobile Applications (IJESMA),* 9(3), 38-61.

Amoroso, D., Lim, R., & Roman, F. L. (2021). The effect of reciprocity on mobile wallet intention: A study of filipino consumers. *International Journal of Asian Business and Information Management (IJABIM),* 12(2), 57-83.

Amoroso, D. L., & Magnier-Watanabe, R. (2012). Building a research model for mobile wallet consumer adoption: the case of mobile Suica in Japan. *Journal of Theoretical and Applied Electronic Commerce Research,* 7(1), 94-110.

Anderson, J. L., Jolly, L. D., & Fairhurst, A. E. (2007). Customer relationship management in retailing: A content analysis of retail trade journals. *Journal of Retailing and Consumer Services,* 14 (6), 394–399.

Anshari, M., Arine, M. A., Nurhidayah, N., Aziyah, H., & Salleh, M. H. A. (2021). Factors influencing individual in adopting eWallet. *Journal of Financial Services Marketing,* 26(1), 10-23.

Aparna, H., Karthika, S., & Rajalakshmi, V.R. (2019). A study on the digital wallet usage among citizens of Kochi using FP-growth algorithm. *International Journal of Recent Technology and Engineering,* 7(6), 1315-1322.

Ariguzo, G. C., & White, D. S. (2013). Exploring demographic differences in the adoption of mobile money: M-PESA in Kenya. *International Journal of Electronic*

Marketing and Retailing, 5(4), 340-358.

Armitage, C. J., & Conner, M. (2001). Efficacy of the theory of planned behaviour: A meta-analytic review. *British Journal of Social Psychology,* 40(4), 471-499.

Astari, A., Yasa, N., Sukaatmadja, I., & Giantari, I. (2022). Integration of technology acceptance model (TAM) and theory of planned behavior (TPB): An e-wallet behavior with fear of covid-19 as a moderator variable. *International Journal of Data and Network Science,* 6(4), 1427-1436.

Audretsch, D. B., Eichler, G. M., & Schwarz, E. J. (2022). Emerging needs of social innovators and social innovation ecosystems. *International Entrepreneurship and Management Journal,* 1-38.

Bagla, R. K., & Sancheti, V. (2018). Gaps in customer satisfaction with digital wallets: challenge for sustainability. *Journal of Management Development.*

Bagozzi, R. P., & Yi, Y. (1988). On the evaluation of structural equation models. *Journal of the Academy of Marketing Science,* 16(1), 74-94.

Bailey, A. A., Bonifield, C. M., Arias, A., & Villegas, J. (2022). Mobile payment adoption in Latin America. *Journal of Services Marketing.* (ahead-of-print).

Bailey, A. A., Pentina, I., Mishra, A. S., & Ben Mimoun, M. S. (2017). Mobile payments adoption by US consumers: an extended TAM. *International Journal of Retail & Distribution Management,* 45(6), 626-640.

Bauer, C., Garaus, M., Strauss, C., & Wagner, U. (2018). Research directions for digital signage systems in retail. *Procedia Computer Science*, 141, 503-506.

Berman, B., Katona, Z., & Zauberman, G. (2018). The role of search in online marketplaces. *Journal of Marketing Research,* 55(6), 832-849.

Bezovski, Z. (2016). The future of the mobile payment as electronic payment system. *European Journal of Business and Management,* 8(8), 127-132.

Bhatia, P., Arora, A., & Jain, M. (2019). Security features and concerns of virtual credit cards. *International Journal of Innovative Technology and Exploring Engineering,* 8(9), 631-635.

Bommer, W. H., Rana, S., & Milevoj, E. (2022). A meta-analysis of eWallet adoption using the UTAUT model. *International Journal of Bank Marketing,* 40, 791-819.

Boro, K. (2015). Prospects and challenges of technological innovation in banking industry of North East India. *The Journal of Internet Banking and Commerce,* 20(3).

Botsman, R., & Rogers, R. (2010). What's mine is yours: The rise of collaborative consumption. Harper Collins.

Boztuğ, Y., & Reutterer, T. (2008). A combined approach for segment-specific market basket analysis. *European Journal of Operational Research,* 187(1), 294-312.

Brem, A., Maier, M., & Wimschneider, C. (2016). Competitive advantage through innovation: the case of Nespresso. *European Journal of Innovation Management.*

Brik, B., Bettayeb, B., Sahnoun, M. H., & Duval, F. (2019). Towards predicting system disruption in industry 4.0: machine learning-based approach. *Procedia Computer Science,* 151, 667-674.

Brill, T. M., Munoz, L., & Miller, R. J. (2019). Siri, Alexa, and other digital assistants: a study of customer satisfaction with artificial intelligence applications. *Journal of Marketing Management,* 35(15-16), 1401-1436.

Byrne, B. M. (2001). Structural Equation Modelling with AMOS, Basics Concepts, Applications, and Programming. Hillsdale, New Jersey: Lawrence Erlbaum Associates.

Budiarani, V. H., Maulidan, R., Setianto, D. P., & Widayanti, I. (2021). The kano model: how the pandemic influences customer satisfaction with digital wallet services in Indonesia. *Journal of Indonesian Economy and Business: JIEB.,* 36(1), 62-82.

Burtch, G., Carnahan, S., & Greenwood, B. N. (2018). Can you gig it? An empirical examination of the gig economy and entrepreneurial activity. *Management Science,* 64(12), 5497-5520.

Cachada, A., Barbosa, J., Leitño, P., Gcraldcs, C. A., Deusdado, L., Costa, J., ... & Romero, L. (2018). Maintenance 4.0: Intelligent and predictive maintenance system architecture. *23rd International Conference on Emerging Technologies and Factory Automation (ETFA),* 1, 139-146. IEEE.

Campbell, D., & Singh, C. B. (2017). A study of customer innovativeness for the mobile wallet acceptance in Rajasthan. *Pacific Business Review International,* 10(6), 7-15.

Caro, F., & Sadr, R. (2019). The Internet of Things (IoT) in retail: Bridging supply and demand. *Business Horizons,* 62(1), 47-54.

Chaddha, P. R. I. Y. A. N. K. A., Agarwal, B. H. A. W. A., & Zareen, A. R. H. I. (2021). Investigating the effect of the credibility of celebrity endorsement on the intent of consumers to buy digital wallets in India. *Indian J. Econ. Bus,* 20(1), 63-79.

Chamhuri, N., & Batt, P J. (2013). Segmentation of Malaysian shoppers by store choice behaviour in their purchase of fresh meat and fresh produce. *Journal of Retailing and Consumer Services,* 20, 516-528.

Chang, V., Baudier, P., Zhang, H., Xu, Q., Zhang, J., & Arami, M. (2020). How Blockchain can impact financial services–The overview, challenges and recommendations from expert interviewees. *Technological Forecasting and Social Change,* 158, 120166.

Chang, Y. W., & Chen, J. (2021). What motivates customers to shop in smart shops? The impacts of smart technology and technology readiness. *Journal of Retailing and Consumer Services,* 58, 102325.

Chauhan, V., Yadav, R., & Choudhary, V. (2022). Adoption of electronic banking services in India: an extension of UTAUT2 model. *Journal of Financial Services Marketing,* 27(1), 27-40.

Chawla, D., & Joshi, H. (2019). Consumer attitude and intention to adopt mobile wallet in India–An empirical study. *International Journal of Bank Marketing.*

Chawla, D., & Joshi, H. (2020). The moderating role of gender and age in the adoption of mobile wallet. *Foresight,* 22, 483-504.

Chawla, D., & Joshi, H. (2021). Importance-performance map analysis to enhance the performance of attitude towards mobile wallet adoption among Indian consumer segments. *Aslib Journal of Information Management,* 73, 946-966.

Chen, F. L., Ou, T. Y. (2011). Sales forecasting system based on Gray extreme learning machine with Taguchi method in retail industry. *Expert System with Application,* 38, 1336-1345.

Chen, J. V., Huang, C.-M., Chiang, Y.-H., & Chen, S.-C. (2019). Consumers' Acceptance of Virtual Reality Shopping: An Integrative Model of Technology Acceptance and Uses Theory. *Journal of Retailing and Consumer Services,* 49, 272-283.

Chen, L., Wang, Y., & Yang, S. (2018). Influence of perceived risk on consumer adoption of mobile payment services: An application of UTAUT2. *International Journal of Information Management,* 43, 1-12.

Chen, L. H., & Yeh, S. S. (2005). The effects of consumer knowledge on message processing of electronic word-of-mouth via online consumer reviews. *Electronic Commerce Research and Applications,* 4(4), 452-461.

Chen, M.F., & Lin, N.P. (2018). Incorporation of health consciousness into the technology readiness and acceptance model to predict app download and usage intentions. *Internet Res.,* 28, 351–373.

Chen, S., & Li, X. (2017). An empirical study of factors influencing online shopping behavior of consumers in China. *Journal of Retailing and Consumer Services,* 35, 150-162.

Chen, S.-C., Li, S.-Y., & Hong, Z.-W. (2017). Exploring consumers' intention to use virtual reality shopping: The moderating role of innovativeness. *Journal of Retailing and Consumer Services,* 39, 221-228.

Chen, Y. H., Wang, Y. S., & Tang, T. I. (2019). Understanding the intention to use mobile shopping applications: An integration of TAM and TPB with ITM. *Journal of Retailing and Consumer Services,* 47, 164-175.

Chen, Y.-L., Tang, K., Shen, R.-J., & Hu, Y.-H. (2005). Market basket analysis in a multiple store environment. *Decision Support Systems,* 40 (2), 339–354.

Chetioui, Y., Lebdaoui, H., & Chetioui, H. (2021). Factors influencing consumer attitudes toward online shopping: the mediating effect of trust. *EuroMed Journal of Business,* 16(4), 544-563.

Chi, T. (2018). Understanding Chinese consumer adoption of apparel mobile commerce: An extended TAM approach. *Journal of Retailing and Consumer Services,* 44, 274-284.

Chiang, L. L &Yang, C. S. (2018). Does country-of-origin brand personality generate retail customer lifetime value? A Big Data analytics approach. *Technological Forecasting & Social Change,* 130, 177-187.

Chin,W. W. (2010). How to write up and report PLS analyses. InV. Esposito Vinzi, W.W. Chin, J. Henseler, & H. Wang (Eds.), Handbook of partial least squares: Concepts, methods and application (pp. 645–689). New York: Springer.

Chohan, F., Aras, M., Indra, R., Wicaksono, A., &Winardi, F. (2022). Building Customer Loyalty In Digital Transaction Using QR Code: Quick Response Code Indonesian Standard (QRIS). *Journal of Distribution Science,* 20(1), 1-11.

Choi, S. H., Yang, Y. X., Yang, B., & Cheung, H. H. (2015). Item-level RFID for enhancement of customer shopping experience in apparel retail. *Computers in Industry,* 71, 10-23.

Chopdar, P. K., & Balakrishnan, J. (2020). Consumers response towards mobile commerce applications: SOR approach. *International Journal of Information Management,* 53, 102106.

Chopdar, P. K., Korfiatis, N., Sivakumar, V. J., & Lytras, M. D. (2018). Mobile shopping apps adoption and perceived risks: A cross-country perspective utilizing the Unified Theory of Acceptance and Use of Technology. *Computers in Human Behavior,* 86, 109-128.

Chou, S. F., Horng, J. S., Liu, C. H. S., & Lin, J. Y. (2020). Identifying the critical factors of customer behavior: An integration perspective of marketing strategy and components of attitudes. *Journal of Retailing and Consumer Services,* 55, 102113.

Choudhary, P., & Choudhary, P. (2020). Mobile wallet business model: A systematic review of the literature. *Journal of Retailing and Consumer Services,* 56, 102135.

Chuttur, M. Y. (2009). Overview of the Technology Acceptance Model: Origins, Developments and Future Directions. Indiana University, USA.

Ciabattoni, L., Frontoni, E., Liciotti, D., Paolanti, M., & Romeo, L. (2017). A sensor fusion approach for measuring emotional customer experience in an intelligent retail environment. *7th International Conference on Consumer Electronics-Berlin (ICCE-Berlin),* 67-68. IEEE.

Cil, I. (2012). Consumption universes based supermarket layout through associa- tion rule mining and multidimensional scaling. *Expert Systems with Applications,* 39 (10), 8611–8625.

Cruz, E., Orts-Escolano, S., Gomez-Donoso, F., Rizo, C., Rangel, J. C., Mora, H., & Cazorla, M. (2019). An augmented reality application for improving shopping experience in large retail stores. *Virtual Reality,* 23(3), 281-291.

Dalzochio, J., Kunst, R., Pignaton, E., Binotto, A., Sanyal, S., Favilla, J., & Barbosa, J. (2020). Machine learning and reasoning for predictive maintenance in Industry 4.0: Current status and challenges. *Computers in Industry,* 123, 103298.

Damanpour, F., & Schneider, M. (2006). Phases of the adoption of innovation in organizations: Effects of environment, organization and top managers. *British Journal of Management,* 17(3), 215-236.

Dauda, S. Y., & Lee, J. (2015). Technology adoption: A conjoint analysis of consumers′ preference on future online banking services. *Information Systems,* 53, 1-15.

David, S., & Kathrine, J.W. (2019). An investigative report on encryption based security mechanisms for e-wallets. *Journal of Scientific and Technology Research,* 8(10), 1755-1769.

Davis, F. D. (1986). A technology acceptance model for empirically testing new end-user information systems: Theory and results. *Doctoral Dissertation,* Massachusetts Institute of Technology.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 13(3), 319-340.

Debnath, S., & Bose, I. (2021). Business models of mobile payment systems: A review of literature. *Journal of Retailing and Consumer Services,* 60, 102424.

Deloitte. (2019). *Global Mobile Consumer Survey 2019: The dawn of 5G*. Retrieved from https://www2.deloitte.com/global/en/pages/technology-media-and-telecommunications/articles/glob al-mobile-consumer-survey-2019.html

De Luna, I. R., Liébana-Cabanillas, F., Sánchez-Fernández, J., & Muñoz-Leiva, F. (2019). Mobile payment is not all the same: The adoption of mobile payment systems depending on the technology applied. *Technological Forecasting and Social Change*, 146, 931-944.

Demirgüç-Kunt, A., & Klapper, L. (2012). Mobile banking: shedding light on its adoption and impact on financial inclusion. *World Bank Policy Research Working Paper*, (6274).

Dennehy, D., & Sammon, D. (2015). Trends in mobile payments research: A literature review. *Journal of Innovation Management,* 3(1), 49-61.

De Roure, C., Page, K., Sorniotti, A., & Vo, B. (2018). Peer-to-peer lending and financial innovation in the UK since 2005: An empirical analysis. *Journal of Banking & Finance,* 97, 71-91.

De Vries, G., Gensler, S., & Leeflang, P. S. (2017). Popularity of brand posts on brand fan pages: An investigation of the effects of social media marketing. *Journal of Interactive Marketing*, 38, 70-81.

Dhanabalan, T., & Sathish, A. (2018). Transforming Indian industries through artificial intelligence and robotics in industry 4.0. *Int. J. Mech. Eng. Technol.*, 9, 835–845.

Dua, A., & Dhir, A. (2020). Examining the business models of mobile wallet firms in India: A comparative analysis. *International Journal of Bank Marketing,* 38(5),

1025-1040.

Estiyanti, N. M., Agustia, D., Mulia, R. A., Alfarisyi, R., Frandha, R., Hidayanto, A. N., & Kurnia, S. (2021). The impact of perceived usability on mobile wallet acceptance: a case of Gopay Indonesia. *International Journal of Innovation and Learning*, 30(2), 154-174.

Fanuel, P. N., & Fajar, A. N. (2021). Digital wallet war in Asia: Finding the drivers of digital wallet adoption. *Journal of Payments Strategy & Systems*, 15(1), 79-91.

Farquad, M. A. H., Ravi, V., & Raju, S. B. (2014). Churn prediction using comprehensible support vector machine: An analytical CRM application. *Applied Soft Computing*, 19, 31-40.

Fishbein, M. & Ajzen, I. (1975), Belief, attitude, intention and behavior: An introduction to theory and research,Addison-Wesley, Reading, MA.

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, 18(1), 39-50.

Foster, B., Hurriyati, R., & Johansyah, M. D. (2022). The Effect of Product Knowledge, Perceived Benefits, and Perceptions of Risk on Indonesian Student Decisions to Use E-Wallets for Warunk Upnormal. *Sustainability*, 14(11), 6475.

Füller, J., Hutter, K., Wahl, J., Bilgram, V., & Tekic, Z. (2022). How AI revolutionizes innovation management–Perceptions and implementation preferences of AI-based innovators. *Technological Forecasting and Social Change*, 178, 121598.

Gao, J., Wang, C., & Li, X. (2021). Factors affecting the adoption of virtual credit cards in China. *Sustainability*, 13(3), 1128.

Gao, Y. F., Liang, Y. S., Liu, Y., Zhan, S. B., & Ou, Z. W. (2009). A neural-network-based forecasting algorithm for retail industry. *International Conference on Machine Learning and Cybernetics*, 2, 919-924.

Gao, Y., Zhang, X., Li, X., & Wang, T. (2020). Credit scoring with deep learning in fintech: A review. *Journal of Business Research*, 117, 1-16.

Garg, V., & Kim, J. Y. (2018). FinTech payment solutions: A critical review of current developments and future prospects. *Journal of Financial Services Research*, 54(1), 1-29.

Garrouch, K. (2021). Does the reputation of the provider matter? A model explaining the

continuance intention of mobile wallet applications. *Journal of Decision Systems*, 30(2-3), 150-171.

Gefen, D., Straub, D., & Boudreau, M. (2000). Structural Equation Modeling Techniques and Regression: Guidelines for Research Practice. *Communications of the Association for Information Systems*, 7(7), 1-78

George, A., & Sunny, P. (2021). Developing a research model for mobile wallet adoption and usage. *IIM Kozhikode Society & Management Review*, 10(1), 82-98.

George, A., & Sunny, P. (2022). Why do people continue using mobile wallets? An empirical analysis amid COVID-19 pandemic. *Journal of Financial Services Marketing*, 1-15.

Gilboa, S. (2009). A segmentation study of Israeli mall customers. *Journal of Retailing and Consumer Services*, 16, 135-144.

Gill, S. S., Tuli, S., Xu, M., Singh, I., Singh, K. V., Lindsay, D., & Garraghan, P. (2019). Transformative effects of IoT, Blockchain and Artificial Intelligence on cloud computing: Evolution, vision, trends and open challenges. *Internet of Things*, 8, 100118.

Godoe, P., & Johansen, T.S. (2012). Understanding adoption of new technologies: technology readiness and technology acceptance as an integrated concept. *J. Eur. Psychol. Stud.*, 3 (1), 38–52.

Gong, G., Tang, Q., & Xu, Y. (2019). Loan portfolio diversification and platform stability in peer-to-peer lending. *Journal of Business Venturing*, 34(1), 1-18.

Gong, X., Cheung, C. M., Zhang, K. Z., Chen, C., & Lee, M. K. (2020). Cross-side network effects, brand equity, and consumer loyalty: evidence from mobile payment market. *International Journal of Electronic Commerce*, 24(3), 279-304.

Gozman, D., Liebenau, J., & Mangan, J. (2018). The innovation mechanisms of fintech start-ups: insights from SWIFT's innotribe competition. *Journal of Management Information Systems*, 35(1), 145-179.

Grewal, D., Monroe, K. B., & Krishnan, R. (1998). The effects of price-comparison advertising on buyers' perceptions of acquisition value, transaction value, and behavioral intentions. *Journal of Marketing*, 62(2), 46-59.

Grover, P., Kar, A. K., & Ilavarasan, P. V. (2017). Understanding nature of social media usage by mobile wallets service providers–an exploration through SPIN

framework. *Procedia Computer Science,* 122, 292-299.

Grover, P., & Kar, A. K. (2020). User engagement for mobile payment service providers–introducing the social media engagement model. *Journal of Retailing and Consumer Services,* 53, 101718.

Grunert, J., Weber, C., & Beck, R. (2020). Lending platform business models: A review and future research directions. *Electronic Markets,* 30(1), 1-19.

Gupta, R. K. (2022). Adoption of mobile wallet services: an empirical analysis. International Journal of Intellectual Property Management, 12(3), 341-353.

Gupta, A., Yousaf, A., & Mishra, A. (2020). How pre-adoption expectancies shape post-adoption continuance intentions: An extended expectation-confirmation model. *International Journal of Information Management,* 52, 102094.

Gupta, S., Dhingra, S., Tanwar, S., & Aggarwal, R. (2022). What Explains the Adoption of Mobile Wallets? A Study from Merchants' Perspectives. *International Journal of Human–Computer Interaction,* 1-13.

Gursoy, D., Chi, O. H., Lu, L., & Nunkoo, R. (2019). Consumers acceptance of artificially intelligent (AI) device use in service delivery. *International Journal of Information Management,* 49, 157-169.

Hair Jr, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2014). Multivariate Data Analysis. 7E., Pearson., USA.

Hair Jr, J. F., Bush, R. P., & Ortinau, D. J. (2000). Marketing Research: A Practical Approach for the New Millennium, Boston: Irwin/McGraw-Hill.

Han, S., Ye, Y., Fu, X., & Chen, Z. (2014). Category role aided market segmentation approach to convenience store chain category management. *Decision Support Systems,* 57 (1), 296–308.

Hartono, E., Holsapple, C. W., Kim, K. Y., Na, K. S., & Simpson, J. T. (2014). Measuring perceived security in B2C electronic commerce website usage: A respecification and validation. *Decision Support Systems,* 62, 11-21.

Hassan, M. A., & Shukur, Z. (2021). Device Identity-Based User Authentication on Electronic Payment System for Secure E-Wallet Apps. *Electronics,* 11(1), 4.

Hegde, J., & Rokseth, B. (2020). Applications of machine learning methods for engineering risk assessment–A review. *Safety Science,* 122, 104492.

Heo, M., & Lee, K. J. (2018). Chatbot as a new business communication tool: The case

of naver talktalk. *Business Communication Research and Practice,* 1(1), 41-45.

Hoang, H., & Le, T. T. (2020). The Role of Promotion in Mobile Wallet Adoption–A Research in Vietnam. *Advances in Science, Technology and Engineering Systems,* 5(6), 290-298.

Holdack, E., Lurie-Stoyanov, K., & Fromme, H. F. (2022). The role of perceived enjoyment and perceived informativeness in assessing the acceptance of AR wearables. *Journal of Retailing and Consumer Services,* 65, 102259.

Holden, R. J., Karsh, B. T., & Or, C. K. (2018). A theoretical model of health information technology usage and satisfaction among medical residents. *Journal of the American Medical Informatics Association,* 25(1), 28-35.

Hopalı, E., & Vayvay, Ö. (2018). Industry 4.0 as the last industrial revolution and its opportunities for developing countries. In Analyzing the Impacts of Industry 4.0 in Modern Business Environments (pp. 65-80). IGI Global.

Hopalı, E., Vayvay, Ö., Kalender, Z. T., Turhan, D., & Aysuna, C. (2022). How Do Mobile Wallets Improve Sustainability in Payment Services? A Comprehensive Literature Review. *Sustainability,* 14(24), 16541.

Hor, H. L., Wong, W. L., Ho, S. K., Tan, J. H., Teo, S. X., & Foo, P. Y. (2021). The leading edge of NFC mobile wallet adoption: an empirical analysis from an emerging economy's perspective. *International Journal of Services, Economics and Management,* 12(3), 228-253.

Horsky, D., & Simon, L. S. (2015). Continuous time innovation diffusion model with application to pharmaceutical sales. *Marketing Science,* 34(3), 395-417.

Hou, J. L., & Chen T. G. (2011). An RFID-based shopping service system for retailers. *Advanced Engineering Informatics,* 25, 103-115.

Hoyer, W. D., Kroschke, M., Schmitt, B., Kraume, K., & Shankar, V. (2020). Transforming the customer experience through new technologies. *Journal of Interactive Marketing,* 51, 57-71.

Hu, X., Huang, L., Zhang, Y., & Wang, C. (2019). Exploring consumer intention to use smart retail technologies: Evidence from the US and China. *Journal of Retailing and Consumer Services,* 51, 217-227.

Huang, C., & Shen, C. (2019). The impact of mobile point-of-sale (mPOS) on the retail industry: A case study of Taiwan. *Journal of Retailing and Consumer Services,* 51,

410-417.

Huang, R., Kim, M., & Lennon, S. (2022). Trust as a second-order construct: Investigating the relationship between consumers and virtual agents. *Telematics and Informatics,* 70, 101811.

Huber, J., & Stuckenschmidt, H. (2020). Daily retail demand forecasting using machine learning with emphasis on calendric special days. *International Journal of Forecasting,* 36(4), 1420-1438.

Humbani, M., & Wiese, M. (2018). A cashless society for all: Determining consumers' readiness to adopt mobile payment services. *Journal of African Business,* 19(3), 409-429.

Hwang, J., & Lyu, S. O. (2020). Relationships among green image, consumer attitudes, desire, and customer citizenship behavior in the airline industry. *International Journal of Sustainable Transportation,* 14(6), 437-447.

Ilankumaran, G. (2019). Payment System Indicators of Digital Banking Ecosystem in India. *Clearing,* 1273(1), 114-06.

Iqbal, S., Irfan, M., Ahsan, K., Hussain, M. A., Awais, M., Shiraz, M., ... & Alghamdi, A. (2020). A novel mobile wallet model for elderly using fingerprint as authentication factor. *IEEE Access,* 8, 177405-177423.

Jaiswal, D., Kaushal, V., Mohan, A., & Thaichon, P. (2022). Mobile wallets adoption: pre-and post-adoption dynamics of mobile wallets usage. *Marketing Intelligence & Planning.*

Jiao, Z., Shahid, M. S., Mirza, N., & Tan, Z. (2021). Should the fourth industrial revolution be widespread or confined geographically? A country-level analysis of fintech economies. *Technological Forecasting and Social Change,* 163, 120442.

Jiang, F., & Leung, C. (2015). A data analytic algorithm for managing, querying, and processing uncertain big data in cloud environments. *Algorithms,* 8(4), 1175-1194.

Jin, C. (2013). The perspective of a revised TRAM on social capital building: the case of Facebook usage. *Inf. Manag.,* 50, 162–168.

Jocevski, M., Ghezzi, A., & Arvidsson, N. (2020). Exploring the growth challenge of mobile payment platforms: A business model perspective. *Electronic Commerce Research and Applications,* 40, 100908.

Joreskog, K & Sorbom, D. (1993). Lisrel 8: Structural Equation Modeling with the

Simplis Command Language, Scientific Software International, Inc.

Junadi, S. (2015). A model of factors influencing consumer's intention to use e-payment system in Indonesia. *Procedia Computer Science,* 59, 214-220.

Juniper Research. (2017). *mPOS terminals to process 40% of all retail transactions by 2021*. Retrieved from https://www.juniperresearch.com/press/press-releases/mpos-terminals-to-process-40-of-all-retail-transact

Juniper Research. (2018). *Mobile Wallets: Service Provider Analysis, Market Opportunities & Forecasts 2018-2022*. Retrieved from https://www.juniperresearch.com/document-library/white-papers/mobile-wallets-service-provider-analysis

Kahn, B.E., Inman, J.J., & Verhoef, P.C. (2018). Introduction to special issue: consumer response to the evolving retailing landscape. *J. Assoc. Consum. Res.*, 3, 255–259.

Kaisler, S., Armour, F., Espinosa, J. A., & Money, W. (2013). Big data: Issues and challenges moving forward. *46th Hawaii International Conference on System Sciences,* 995-1004. IEEE.

Karsen, M., Chandra, Y. U., & Juwitasary, H. (2019). Technological factors of mobile payment: A systematic literature review. *Procedia Computer Science,* 157, 489-498.

Kato, N., Osone, H., Oomori, K., Ooi, C. W., & Ochiai, Y. (2019). Gans-based clothes design: Pattern maker is all you need to design clothing. *10th Augmented Human International Conference*, 1-7.

Katsikeas, C. S., Samiee, S., & Theodosiou, M. (2016). New product development in international markets. *Journal of International Marketing,* 24(2), 1-20.

Kaur, P., Dhir, A., Bodhi, R., Singh, T., & Almotairi, M. (2020). Why do people use and recommend m-wallets? *Journal of Retailing and Consumer Services,* 56, 102091.

Kaushik, A. K., Agrawal, A. K., & Rahman, Z. (2015). Tourist behaviour towards self-service hotel technology adoption: Trust and subjective norm as key antecedents. *Tourism Management Perspectives*, 16, 278-289.

Kapoor, A., Sindwani, R., & Goel, M. (2020). Mobile wallets: Theoretical and empirical analysis. *Global Business Review,* 0972150920961254.

Kapoor, A., Sindwani, R., & Goel, M. (2021). Ranking Mobile Wallet Service Providers Using Fuzzy Multi-Criteria Decision-Making Approach. *International Journal of E-Business Research (IJEBR),* 17(4), 19-39.

Karahanna, E., Straub, D. W., & Chervany, N. L. (2006). Information technology adoption across time: A cross-sectional comparison of pre-adoption and post-adoption beliefs. *MIS Quarterly*, 30(3), 55-78.

Kavitha, K., & Kannan, D. D. (2020). Factors Influencing Consumers Attitude Towards Mobile Payment Applications. *International Journal of Management*, 11(4).

Kavitha, R., Rajeswari, R., Mukherjee, P., Rout, S., & Patra, S. S. (2022). Performance Measures of Blockchain-Based Mobile Wallet Using Queueing Model. *Intelligent Systems and Sustainable Computing*, 269-277.

Keiningham, T., Aksoy, L., Bruce, H. L., Cadet, F., Clennell, N., Hodgkinson, I. R., & Kearney, T. (2020). Customer experience driven business model innovation. *Journal of Business Research*, 116, 431-440.

Keramati, A., Ghaneei, H., & Mirmohammadi, S. M. (2016). Developing a prediction model for customer churn from electronic banking services using data mining. *Financial Innovation*, 2(1), 1-13.

Khade, A. A. (2016). Performing customer behavior analysis using big data analytics. *Procedia Computer Science*, 79, 986-992.

Kim, H. J., & Park, J. W. (2019). Influences of food bloggers on consumers' intention to purchase restaurant food: Application of the theory of planned behavior and celebrity endorsement. *Journal of Hospitality and Tourism Technology*, 10(4), 623-640.

Kim, H. K., Kim, J. K., & Chen, Q. Y. (2012). A product network analysis for extending the market basket analysis. *Expert Systems with Applications*, 39 (8), 7403–7410.

Kim, J., Yang, K., Min, J., & White, B. (2022). Hope, fear, and consumer behavioral change amid COVID-19: Application of protection motivation theory. *International Journal of Consumer Studies*, 46(2), 558-574.

Kim, T., & Chiu, W. (2019). Consumer acceptance of sports wearable technology: the role of technology readiness. *Int. J. Sports Mark. Spons.*, 20, 109–126.

Kolapo, T. F., & Adeniran, O. A. (2020). The adoption of mobile point of sale (mPOS) in the Nigerian retail industry. *Journal of Retailing and Consumer Services*, 54, 102051.

Koloor, H. R., Langehbiz, M. N., & Mahmoudi, A. (2015). Submission Structural Equation Modeling (SEM) of Factors Affecting Competitiveness, 8(September),

343–356.

Korniotis, G. M., & Kumar, A. (2018). Robo-advisors: Investment management for the masses? *Journal of Financial Economics*, 128(2), 251-265.

Kotler, P., & Armstrong, G. (2012). Principles of Marketing, fourteenth ed. Pearson, New Jersey.

Kowalczuk, P., Siepmann, C., & Adler, J. (2021). Cognitive, affective, and behavioral consumer responses to augmented reality in e-commerce: A comparative study. *Journal of Business Research*, 124, 357-373.

KPMG. (2019). *The Pulse of Fintech Q4 2018.* Retrieved from https://home.kpmg/content/dam/kpmg/xx/pdf/2019/01/pulse-of-fintech-q4-2018.pdf

Kramm, J., & Kräussl, R. (2018). The impact of robo-advisors on the investment advisory industry. *Journal of Business Research*, 89, 336-343.

Kronberger, G., & Affenzeller, M. (2011). Market basket analysis of retail data: supervised learning approach. *International Conference on Computer Aided Systems Theory*, 464-471. Springer, Berlin, Heidelberg.

Kumar, A., Adlakaha, A., & Mukherjee, K. (2018). The effect of perceived security and grievance redressal on continuance intention to use M-wallets in a developing country. *International Journal of Bank Marketing.*

Kumar, A., & Mukherjee, A. (2013). Shop while you talk: determinants of purchase intentions through a mobile device. *Int J Mobile Market*., 8 (1), 23–37.

Kumar, R., Ratra, V., & Mandava, S. (2022). Mobile wallet payments in the time of COVID-19: The Indian experience. *Journal of Payments Strategy & Systems*, 16(1), 7-16.

Kumar, V., Anand, A., & Song, H. (2017). Future of retailer profitability: An organizing framework. *Journal of Retailing*, 93(1), 96-119.

Kumar, V., Lai, K. K., Chang, Y. H., Bhatt, P. C., & Su, F. P. (2020). A structural analysis approach to identify technology innovation and evolution path: a case of m-payment technology ecosystem. *Journal of Knowledge Management.*

Kumar, V., Nim, N., & Sharma, A. (2019). Driving growth of Mwallets in emerging markets: A retailer's perspective. *Journal of the Academy of Marketing Science*, 47(4), 747-769.

Kuo, Y.-F., Wu, C.-M., & Deng, W.-J. (2018). Exploring the factors influencing

customers' adoption of self-service technologies in the retail context. *International Journal of Information Management,* 39, 176-186.

Ładyżyński, P., Żbikowski, K., & Gawrysiak, P. (2019). Direct marketing campaigns in retail banking with the use of deep learning and random forests. *Expert Systems with Applications,* 134, 28-35.

Laukkanen, T., Sinkkonen, S., & Laukkanen, P. (2021). Determinants of mobile payment adoption: An empirical study. *Journal of Retailing and Consumer Services,* 58, 102273.

Lee, C. K. H. (2017). A GA-based optimisation model for big data analytics supporting anticipatory shipping in Retail 4.0. *International Journal of Production Research,* 55(2), 593-605.

Lee, J., Koo, C., & Kim, K. (2018). Exploring determinants of mobile wallet adoption: A value perspective. *Journal of Retailing and Consumer Services,* 43, 1-10.

Lee, J., Ryu, M. H., & Lee, D. (2019). A study on the reciprocal relationship between user perception and retailer perception on platform-based mobile payment service. *Journal of Retailing and Consumer Services,* 48, 7-15.

Lee, V. H., Hooy, C. W., & Hew, T. S. (2019). An empirical investigation of factors influencing online purchase intention in Malaysia. *Journal of Marketing Communications,* 25(4), 371-386.

Lee, Y. Y., Gan, C. L., & Liew, T. W. (2022). Do E-wallets trigger impulse purchases? An analysis of Malaysian Gen-Y and Gen-Z consumers. *Journal of Marketing Analytics,* 1-18.

León, C. (2021). The adoption of a mobile payment system: the user perspective. *Latin American Journal of Central Banking,* 2(4), 100042.

Leong, L. Y., Hew, T. S., Ooi, K. B., & Wei, J. (2020). Predicting mobile wallet resistance: A two-staged structural equation modeling-artificial neural network approach. *International Journal of Information Management,* 51, 102047.

Lew, S., Tan, G. W. H., Loh, X. M., Hew, J. J., & Ooi, K. B. (2020). The disruptive mobile wallet in the hospitality industry: An extended mobile technology acceptance model. *Technology in Society,* 63, 101430.

Li, X., Cui, L., & Li, D. (2018). Cybersecurity risk and disclosure: Evidence from the P2P lending market. *Journal of Business Research,* 88, 364-372.

Li, X., Huang, L., & Wu, D. (2018). Examining the moderating effect of gender on factors affecting mobile payment adoption: A UTAUT2-based study. *Industrial Management & Data Systems*, 118(3), 619-637.

Liang, X., Liu, Y., & Huang, Y. (2019). Examining mobile payment user adoption from the perspectives of trust and risk: Insights from China. *International Journal of Information Management,* 45, 227-234.

Liljander, V., Gillberg, F., Gummerus, J., & Van Riel, A. (2006). Technology readiness and the evaluation and adoption of self-service technologies. *Journal of Retailing and Consumer Services,* 13(3), 177-191.

Lim, X. J., Ngew, P., Cheah, J. H., Cham, T. H., & Liu, Y. (2022). Go digital: can the money-gift function promote the use of e-wallet apps? *Internet Research.*

Limantara, N., Jovandy, J., Wardhana, A.K., & Steven, Jingga, F. (2021). Evaluation of one of leading Indonesia's digital wallet using the unified theory of acceptance and use of technology. *Indonesian Journal of Electrical Engineering and Computer Science,* 24(2), 1036-1046.

Lin, C. H., Shih, H. Y., & Sher, P. J. (2007). Integrating technology readiness into technology acceptance: The TRAM model. *Psychology & Marketing,* 24(7), 641-657.

Lin, M. (2019). Understanding the fintech lending landscape: The fintech borrower journey map. *Journal of Financial Services Marketing,* 24(2), 63-77.

Liu, J., Luo, X., Yang, J., & Zheng, X. (2019). An Empirical Investigation of Consumer Acceptance and Use of Autonomous Delivery Robots in the Retail Industry. *International Journal of Retail & Distribution Management,* 47(2), 170-186.

Liu, L., Zhou, B., Zou, Z., Yeh, S. C., & Zheng, L. (2018). A smart unstaffed retail shop based on artificial intelligence and IoT. *23rd International Workshop on Computer Aided Modeling and Design of Communication Links and Networks (CAMAD),* 1-4. IEEE.

Lo, K., Liu, F., & Huang, J. (2021). OneFeather Mobile Wallet: A Digital Solution for Indigenous Peoples in Canada? *Accounting Perspectives,* 20(3), 403-419.

Loureiro, A. L., Miguéis, V. L., & da Silva, L. F. (2018). Exploring the use of deep neural networks for sales forecasting in fashion retail. *Decision Support Systems*, 114, 81-93.

Lu, H., Wang, D., Li, X., & Lu, Y. (2020). Investigating consumers' intention to adopt interactive technologies in retail stores: Evidence from a developed market. *Journal of Retailing and Consumer Services*, 53, 101942.

Lu, J., Yao, J. E., & Yu, C. S. (2017). A Model of Customer Adoption of Mobile Payment. *Communications of the Association for Information Systems*, 40(1), 251-276.

Lui, T. K., Zainuldin, M. H., Yii, K. J., Lau, L. S., & Go, Y. H. (2021). Consumer Adoption of Alipay in Malaysia: The Mediation Effect of Perceived Ease of Use and Perceived Usefulness. *Pertanika Journal of Social Sciences & Humanities*, 29(1).

Luo, X., Li, S., Zhang, J., & Shim, S. (2019). How do user reviews and ratings affect product sales? Evidence from online marketplace. *Journal of Retailing*, 95(1), 1-17.

Luo, X., Tong, S., Fang, Z., & Qu, Z. (2019). Frontiers: Machines vs. humans: The impact of artificial intelligence chatbot disclosure on customer purchases. *Marketing Science*, 38(6), 937-947.

Lwin, M. O., Stanforth, N., & Miyazaki, A. D. (2008). Increasing the use of credit and debit cards: The roles of attitudes, efficacy, and self-regulation. *Journal of Applied Social Psychology*, 38(11), 2722-2746.

Ly, H. T. N., Khuong, N. V., & Son, T. H. (2022). Determinants Affect Mobile Wallet Continuous Usage in Covid 19 Pandemic: Evidence From Vietnam. *Cogent Business & Management*, 9(1), 2041792.

Machkour, B., & Abriane, A. (2020). Industry 4.0 and its Implications for the Financial Sector. *Procedia Computer Science*, 177, 496-502.

Madan, K., & Yadav, R. (2016). Behavioural intention to adopt mobile wallet: a developing country perspective. *Journal of Indian Business Research.*

Malik, A., Suresh, S., & Sharma, S. (2019). An empirical study of factors influencing consumers' attitude towards adoption of wallet apps. *International Journal of Management Practice*, 12(4), 426-442.

Malik, A., & Sharma, S. (2021). Antecedents of Wallet App Adoption. *International Journal of Web-Based Learning and Teaching Technologies (IJWLTT)*, 16(2), 12-31.

Manickam, T., Vinayagamoorthi, G., Gopalakrishnan, S., Sudha, M., & Mathiraj, S. P. (2022). Customer Inclination on Mobile Wallets With Reference to Google-Pay and

PayTM in Bengaluru City. *International Journal of E-Business Research (IJEBR)*, 18(1), 1-16.

Martens, M., Roll, O., & Elliott, R. (2017). Testing the technology readiness and acceptance model for mobile payments across Germany and South Africa. *Int. J. Innovat. Technol. Manag.*, 14, 1750033.

Mashelkar, R.A. (2018). Exponential technology, industry 4.0 and future of jobs in India. *Rev. Mark. Integr.*, 10, 138–157.

Mastercard. (2019). *The small business mobile retail report.* Retrieved from https://www.mastercard.us/content/dam/mccom/global/documents/small-business-mobile-retail-report.pdf

Matemba, E. D., Li, G., & Maiseli, B. J. (2022). Consumers' stickiness to mobile payment applications: An empirical study of WeChat wallet. In Research Anthology on Social Media Advertising and Building Consumer Relationships (pp. 731-756). IGI Global.

Mathiraj, S. P., Geeta, S. D. T., & Devi, R. S. (2019). Consumer acuity on select digital wallets. *Int. J. Sci. Technol. Res.*, 8(12), 3551-3556.

Mattila, A. S., & Wirtz, J. (2008). The role of store environmental stimulation and social factors on impulse purchasing. *Journal of Services Marketing*, 22(7), 562-567.

McKinsey & Company. (2016). *The rise and rise of robo-advisory.* Retrieved from https://www.mckinsey.com/industries/financial-services/our-insights/the-rise-and-rise-of-robo-advisory

McKinsey & Company. (2018). *The rise of online marketplaces.* Retrieved from https://www.mckinsey.com/industries/retail/our-insights/the-rise-of-online-marketplaces

Menon, M. M., & Ramakrishnan, H. S. (2019). Revolution of E-wallets usage among Indian millennial. *International Journal of Recent Technology and Engineering*, 8(3), 8306-8312.

Michael, K., & Miller, K. W. (2013). Big data: New opportunities and new challenges. *Computer*, 46(6), 22-24.

Ming, K. L. Y., & Jais, M. (2022). Factors affecting the intention to use e-wallets during the COVID-19 pandemic. *Gadjah Mada International Journal of Business*, 24(1), 82-100.

Mirza, M. N., Nawaz, M. S., Ahsan, U. R., & Gao, Y. (2020). Impact of virtual credit card on customer satisfaction and loyalty: A study of Pakistani customers. *Journal of Reviews on Global Economics,* 9, 387-400.

Mombeuil, C. (2020). An exploratory investigation of factors affecting and best predicting the renewed adoption of mobile wallets. *Journal of Retailing and Consumer Services,* 55, 102127.

Mombeuil, C., & Uhde, H. (2021). Relative convenience, relative advantage, perceived security, perceived privacy, and continuous use intention of China's WeChat Pay: A mixed-method two-phase design study. *Journal of Retailing and Consumer Services,* 59, 102384.

Muhtasim, D. A., Tan, S. Y., Hassan, M. A., Pavel, M. I., & Susmit, S. (2022). Customer Satisfaction with Digital Wallet Services: An Analysis of Security Factors. *International Journal of Advanced Computer Science and Applications,* 13(1).

Nair, A. K., & Bhattacharyya, S. S. (2018). Is sustainability a motive to buy? An exploratory study in the context of mobile applications channel among young Indian consumers. *Foresight.*

Natarajan, T., Balasubramanian, S. A., & Kasilingam, D. L. (2018). The moderating role of device type and age of users on the intention to use mobile shopping applications. *Technology in Society,* 53, 79-90.

Netemeyer, R. G., Bearden, W. O., & Sharma, S. (2003). Scaling procedures: Issues and applications. sage publications.

Nguyen, H.T., & Nguyen, N.T. (2022). Identifying the Factors Affecting the Consumer Behavior in Switching to e-wallets in Payment Activities. *Polish Journal of Management Studies,* 25(1).

Nugraheni, Y. (2013). Data mining using fuzzy method for customer relationship management in retail industry. *Lontar Komputer,* 4 (1), 188-200.

Nurcahyo, R., & Putra, P. A. (2021). Critical factors in indonesia's e-commerce collaboration. *Journal of Theoretical and Applied Electronic Commerce Research,* 16(6), 2458-2469.

Obidat, A., Almahameed, M., & Alalwan, M. (2022). An empirical examination of factors affecting the post-adoption stage of mobile wallets by consumers: A

perspective from a developing country. *Decision Science Letters,* 11(3), 273-288.

Ocak, N., & Cagiltay, K. (2017). Comparison of cognitive modeling and user performance analysis for touch screen mobile interface design. *International Journal of Human–Computer Interaction,* 33(8), 633-641.

Oh, J.C., Yoon, S.J., & Chung, N. (2014). The role of technology readiness in consumers' adoption of mobile internet services between South Korea and China". *Int. J. Mobile Commun.,* 12 (3), 229–248.

Ojo, A. O., Fawehinmi, O., Ojo, O. T., Arasanmi, C., & Tan, C. N. L. (2022). Consumer usage intention of electronic wallets during the COVID-19 pandemic in Malaysia. *Cogent Business & Management,* 9(1), 2056964.

Okonkwo, C. W., Amusa, L. B., Twinomurinzi, H., & Wamba, S. F. (2022). Mobile wallets in cash-based economies during COVID-19. *Industrial Management & Data Systems*, (ahead-of-print).

Omarini, A. E. (2018). Fintech and the future of the payment landscape: the mobile wallet ecosystem. A challenge for retail banks? *Int. J. Financ. Res.*, 9, 97-116.

Pantano, E. (2014). Innovation drivers in retail industry. *International Journal of Information Management,* 34(3), 344-350.

Pantano, E., Rese, A., & Baier, D. (2017). Enhancing the online decision-making process by using augmented reality: A two country comparison of youth markets. *Journal of Retailing and Consumer Services,* 38, 81-95.

Paolanti, M., Romeo, L., Martini, M., Mancini, A., Frontoni, E., & Zingaretti, P. (2019). Robotic retail surveying by deep learning visual and textual data. *Robotics and Autonomous Systems,* 118, 179-188.

Parasuraman, A. (2000). Technology readiness index (TRI): A multiple-item scale to measure readiness to embrace new technologies. *Journal of Service Research,* 2(4), 307-320.

Parasuraman, A., & Colby, C. L. (2015). An updated and streamlined technology readiness index: TRI 2.0. *Journal of Service Research,* 18(1), 59-74.

Park, B., & Bae, J. K. (2015). Using machine learning algorithms for housing price prediction: The case of Fairfax County, Virginia housing data. *Expert Systems with Applications,* 42(6), 2928-2934.

Park, J., Ahn, J., Thavisay, T., & Ren, T. (2019). Examining the role of anxiety and

social influence in multi-benefits of mobile payment service. *Journal of Retailing and Consumer Services,* 47, 140-149.

Park, Y., Chen, J., & Wang, X. (2018). Understanding the effects of SNS information on users' behavioral intention: An integration of social influence and UTAUT2. *Information Technology & People,* 31(1), 34-56.

Persada, S. F., Dalimunte, I., Nadlifatin, R., Miraja, B. A., Redi, A. A. N. P., Prasetyo, Y. T., ... & Lin, S. C. (2021). Revealing the behavior intention of tech-savvy generation Z to use electronic wallet usage: A theory of planned behavior based measurement. *International Journal of Business and Society*, 22(1), 213-226.

Pham, T. T. T., & Ho, J. C. (2015). The effects of product-related, personal-related factors and attractiveness of alternatives on consumer adoption of NFC-based mobile payments. *Technology in Society,* 43, 159-172.

Phan, D. D., & Vogel, D. R. (2010). A model of customer relationship management and business intelligence systems for catalogue and online retailers. *Information & Management,* 47, 69-77.

Phuong, N. N. D., Luan, L. T., Dong, V. V., & Khanh, N. L. N. (2020). Examining customers' continuance intentions towards e-wallet usage: The emergence of mobile payment acceptance in Vietnam. *The Journal of Asian Finance, Economics and Business,* 7(9), 505-516.

Phutela, N., & Altekar, S. (2019). Mobile wallets in India: A framework for consumer adoption. *International Journal of Online Marketing (IJOM),* 9(2), 27-38.

Pillai, R., Sivathanu, B., & Dwivedi, Y. K. (2020). Shopping intention at AI-powered automated retail stores (AIPARS). *Journal of Retailing and Consumer Services,* 57, 102207.

Pookulangara, S., & Koesler, K. (2011). Cultural influence on consumers' usage of social networks and its' impact on online purchase intentions. *Journal of Retailing and Consumer Services,* 18(4), 348-354.

Popescu, C. C. (2018). Improvements in business operations and customer experience through data science and Artificial Intelligence. *International Conference on Business Excellence,* 12 (1), 804-815.

Provost, F., & Fawcett, T. (2013). Data science and its relationship to big data and data-driven decision making. *Big Data,* 1(1), 51-59.

PwC. (2015). *Wealth management 2020: The future of advice.* Retrieved from https://www.pwc.com/gx/en/wealth-management/assets/pwc-wm-2020-the-future-of-advice.pdf

Rahman, M. M., & Haque, M. S. (2020). Business model innovation in mobile payment: A systematic review of the literature. *Journal of Financial Services Marketing,* 25(3), 142-155.

Ramageri, B. M., & Desai, B. L. (2013). Role of data mining in retail sector. *International Journal on Computer Science and Engineering,* 5 (1), 47-50.

Ramli, F. A. A., & Hamzah, M. I. (2021). Mobile payment and e-wallet adoption in emerging economies: A systematic literature review. *Journal of Emerging Economies and Islamic Research,* 9(2), 1-39.

Rana, N. P., Luthra, S., & Rao, H. R. (2022). Assessing challenges to the mobile wallet usage in India: an interpretive structural modelling approach. *Information Technology & People,* (ahead-of-print).

Raza, S. A., Ahmad, M., Amin, M., & Shabbir, R. (2020). Adoption of Mobile Payment Services: A Study of UTAUT2 with Moderating Effects of Gender Differences. *Journal of Open Innovation: Technology, Market, and Complexity,* 6(2), 42.

Reddy, T. T., & Rao, B. M. (2021). Determinants of Continuance Intention to Use Mobile Wallet Services: Light Users vs Heavy Users. *Indian Journal of Marketing,* 51(2), 29-42.

Reddy, T. T., & Rao, B. M. (2019). The moderating effect of gender on continuance intention toward mobile wallet services in India. *Indian Journal of Marketing,* 49(4), 48-62.

Rese, A., Baier, D., Geyer-Schulz, A., & Schreiber, S. (2017). How augmented reality apps are accepted by consumers: A comparative analysis using scales and opinions. *Technological Forecasting and Social Change,* 124, 306-319.

Rese, A., Ganster, L., & Baier, D. (2020). Chatbots in retailers' customer communication: How to measure their acceptance? *Journal of Retailing and Consumer Services,* 56, 102176.

Riegger, A. S., Klein, J. F., Merfeld, K., & Henkel, S. (2021). Technology-enabled personalization in retail stores: Understanding drivers and barriers. *Journal of Business Research,* 123, 140-155.

Rogers, E. M. (1962). Diffusion of innovations. New York: Free Press.

Rogers, E. M. (1983). Diffusion of innovations (3rd ed.). New York: Free Press.

Rogers, E. M. (1995). Diffusion of innovations (4th ed.). New York: Free Press.

Rogers, E. M. (2003). Diffusion of innovations. New York: Free Press.

Roy, S. K., Balaji, M. S., Quazi, A., & Quaddus, M. (2018). Predictors of customer acceptance of and resistance to smart technologies in the retail sector. *Journal of Retailing and Consumer Services,* 42, 147-160.

Ruiz-Martínez, A. (2015). Towards a web payment framework: State-of-the-art and challenges. *Electronic Commerce Research and Applications,* 14(5), 345-350.

Sánchez-Prieto, J. C., Olarte-Pascual, C., & García-Peñalvo, F. J. (2021). The role of attitude and subjective norms in the acceptance of e-learning platforms: An extension of the Technology Acceptance Model. *Interactive Learning Environments,* 1-17.

Sarika, P., & Vasantha, S. (2019). Impact of mobile wallets on cashless transaction. *Int. J. Recent Technol. Eng.,* 7(6), 1164-1171.

Sarmah, R., Dhiman, N., & Kanojia, H. (2021). Understanding intentions and actual use of mobile wallets by millennial: an extended TAM model perspective. *Journal of Indian Business Research,* 13, 361-381.

Schlatt, V., Sedlmeir, J., Feulner, S., & Urbach, N. (2021). Designing a framework for digital KYC processes built on blockchain-based self-sovereign identity. *Information & Management,* 103553.

Schmidt, B., & Wang, L. (2018). Predictive maintenance of machine tool linear axes: A case from manufacturing industry. *Procedia Manufacturing,* 17, 118-125.

Seetharaman, A., Kumar, K. N., Palaniappan, S., & Weber, G. (2017). Factors influencing behavioural intention to use the mobile wallet in Singapore. *Journal of Applied Economics and Business Research,* 7(2), 116-136.

Semerikova, E. (2019). Payment instruments choice of Russian consumers: reasons and pain points. *Journal of Enterprising Communities: People and Places in the Global Economy.*

Senali, M. G., Iranmanesh, M., Ismail, F. N., Rahim, N. F. A., Khoshkam, M., & Mirzaei, M. (2022). Determinants of Intention to Use e-Wallet: Personal Innovativeness and Propensity to Trust as Moderators. *International Journal of*

Human–Computer Interaction, 1-13.

Seong, B. H., & Hong, C. Y. (2022). Corroborating the effect of positive technology readiness on the intention to use the virtual reality sports game "Screen Golf": Focusing on the technology readiness and acceptance model. *Information Processing & Management,* 59(4), 102994.

Shah, B., Ullatil, D. S., & Nagendra, A. (2017). Analysis of the inception, acceptance and future of e-wallets. *International Journal of Applied Business and Economic Research,* 15 (2), 207-215.

Shaikh, A. A., & Karjaluoto, H. (2015). Mobile banking adoption: A literature review. *Telematics and Informatics,* 32(1), 129-142.

Shankar, A., & Behl, A. (2021). How to enhance consumer experience over mobile wallet: a data-driven approach. *Journal of Strategic Marketing,* 1-18.

Sharma, S. K., Mangla, S. K., Luthra, S., & Al-Salti, Z. (2018). Mobile wallet inhibitors: Developing a comprehensive theory using an integrated model. *Journal of Retailing and Consumer Services,* 45, 52-63.

Sharma, D., Aggarwal, D., & Gupta, A. (2019). A study of consumer perception towards mwallets. *Int. Jour. of Sci. & Tech.,* 8(11), 3892-3895.

Shaw, N. (2014). The mediating influence of trust in the adoption of the mobile wallet. *Journal of Retailing and Consumer Services,* 21(4), 449-459.

Shaw, N., Eschenbrenner, B., & Brand, B. M. (2022). Towards a Mobile App Diffusion of Innovations model: A multinational study of mobile wallet adoption. *Journal of Retailing and Consumer Services,* 64, 102768.

Shaw, B., & Kesharwani, A. (2019). Moderating effect of smartphone addiction on mobile wallet payment adoption. *Journal of Internet Commerce,* 18(3), 291-309.

Shekhar, R., & Jaidev, U. P. (2022). Intention to use mobile wallets: an application of the technology acceptance model. *International Journal of Applied Management Science,* 14(3), 258-280.

Shen, X., Zhang, X., Li, D., & Lin, J. (2018). Examining mobile shopping adoption among the elderly: The roles of perceived usefulness, perceived ease of use, and perceived enjoyment. *Journal of Retailing and Consumer Services,* 42, 195-203.

Sheppard, B. H., Hartwick, J., & Warshaw, P. R. (1988). The theory of reasoned action: A meta-analysis of past research with recommendations for modifications and future

research. *Journal of Consumer Research,* 15(3), 325-343.

Shih, Y. Y., Fang, K., & Kuo, Y. C. (2012). The use of a decomposed theory of planned behavior to study internet banking in Taiwan. *Internet Research,* 22(3), 295-313.

Shim, Y., & Shin, D. H. (2016). Analyzing China's fintech industry from the perspective of actor–network theory. *Telecommunications Policy,* 40(2-3), 168-181.

Shin, S., & Lee, W. J. (2014). The effects of technology readiness and technology acceptance on NFC mobile payment services in Korea. *Journal of Applied Business Research (JABR),* 30(6), 1615-1626.

Singh, N., & Sinha, N. (2020). How perceived trust mediates merchant's intention to use a mobile wallet technology. *Journal of Retailing and Consumer Services,* 52, 101894.

Singh, N., Sinha, N., & Liébana-Cabanillas, F. J. (2020). Determining factors in the adoption and recommendation of mobile wallet services in India: Analysis of the effect of innovativeness, stress to use and social influence. *International Journal of Information Management,* 50, 191-205.

Singh, N., Srivastava, S., & Sinha, N. (2017). Consumer preference and satisfaction of M-wallets: a study on North Indian consumers. *International Journal of Bank Marketing.*

Singh, R. P., Turi, A., & Malerba, D. (2007). Grid-based data mining for market basket analysis in the retail sector. *Data Mining VIII: Data, Text and Web Mining and Their Business Applications,* 38, 293.

Singh, S., & Ghatak, S. (2021). Investigating E-Wallet adoption in India: Extending the TAM model. *International Journal of E-Business Research (IJEBR),* 17(3), 42-54.

Slade, E. L., Dwivedi, Y. K., Piercy, N. C., & Williams, M. D. (2015). Modeling consumers' adoption intentions of remote mobile payments in the United Kingdom: extending UTAUT with innovativeness, risk, and trust. *Psychology & Marketing,* 32(8), 860-873.

Slade, E., Williams, M., Dwivedi, Y., & Piercy, N. (2015). Exploring consumer adoption of proximity mobile payments. *Journal of Strategic Marketing,* 23(3), 209-223.

Sobti, N. (2019). Impact of demonetization on diffusion of mobile payment service in India: Antecedents of behavioral intention and adoption using extended UTAUT model. *Journal of Advances in Management Research,* 16, 472-497.

Soe, M. H. (2022). Do They Really Intend to Adopt E-Wallet? Prevalence Estimates for Government Support and Perceived Susceptibility. *Asian Journal of Business Research*, 12(1), 77.

Soodan, V., & Rana, A. (2020). Modeling customers' intention to use e-wallet in a developing nation: Extending UTAUT2 with security, privacy and savings. *Journal of Electronic Commerce in Organizations (JECO)*, 18(1), 89-114.

Square. (2018). *Seller ecosystem: Quarterly report.* Retrieved from https://s1.q4cdn.com/114365585/files/doc_financials/2018/Q3/2018-Q3-Seller-Ecosystem-Quarterly-Report.pdf

Sukwadi, R., Caroline, L. S., & Chen, G. Y. H. (2022). Extended technology acceptance model for Indonesian mobile wallet: Structural equation modeling approach. *Engineering and Applied Science Research*, 49(2), 146-154.

Sun, S., Luo, C., & Chen, J. (2017). A review of natural language processing techniques for opinion mining systems. *Information Fusion*, 36, 10-25.

Surjandari, I., & Seruni, A. (2010). Design of product placement layout in retail shop using market basket analysis. *Makara Journal of Technology*, 9(2), 43-47.

Svetina, M., & Zupancic, J. (2005). How to increase sales in retail with market basket analysis. *Systems Integration*, 14 (2), 418-428.

Taheam, K., Sharma, R., & Goswami, S. (2016). Drivers of digital wallet usage: Implications for leveraging digital marketing. *International Journal of Economic Research*, 13(1), 175-186.

Talwar, M., Talwar, S., Kaur, P., Islam, A. N., & Dhir, A. (2021). Positive and negative word of mouth (WOM) are not necessarily opposites: A reappraisal using the dual factor theory. *Journal of Retailing and Consumer Services*, 63, 102396.

Talwar, S., Dhir, A., Khalil, A., Mohan, G., & Islam, A. N. (2020). Point of adoption and beyond. Initial trust and mobile-payment continuation intention. *Journal of Retailing and Consumer Services*, 55, 102086.

Tamilmani, K., Rana, N. P., Prakasam, N., & Dwivedi, Y. K. (2019). The battle of Brain vs. Heart: A literature review and meta-analysis of "hedonic motivation" use in UTAUT2. *International Journal of Information Management*, 46, 222-235.

Tan, G. W. H., & Teo, T. S. H. (2017). Investigating online purchase intentions of generation Y in Malaysia: From the perspectives of TAM and perceived risk.

Journal of Internet Commerce, 16(2), 164-186.

Tan, S. C., & San Lau, J. P. (2014). Time series clustering: A superior alternative for market basket analysis. *1st International Conference on Advanced Data and Information Engineering (DaEng-2013),* 241-248. Springer, Singapore.

Teng, S., & Khong, K. W. (2021). Examining actual consumer usage of E-wallet: A case study of big data analytics. *Computers in Human Behavior,* 121, 106778.

Teo, A. C., Tan, G. W. H., Ooi, K. B., Hew, T. S., & Yew, K. T. (2015). The effects of convenience and speed in m-payment. *Industrial Management & Data Systems,* 115(2), 311-331.

Thaker, M. T. H., Subramaniam, N. R., Qoyum, A., & Iqbal Hussain, H. (2022). Cashless society, e-wallets and continuous adoption. *International Journal of Finance & Economics,* 27, 1-21.

Thanigan, J., Reddy, S. N., Sethuraman, P., & Rajesh, J. I. (2021). Understanding Consumer Acceptance of M-Wallet Apps: The Role of Perceived Value, Perceived Credibility, and Technology Anxiety. *Journal of Electronic Commerce in Organizations (JECO),* 19(1), 65-91.

Tixier, A. J. P., Hallowell, M. R., Rajagopalan, B., & Bowman, D. (2016). Automated content analysis for construction safety: A natural language processing system to extract precursors and outcomes from unstructured injury reports. *Automation in Construction,* 62, 45-56.

To, A. T., & Trinh, T. H. M. (2021). Understanding behavioral intention to use mobile wallets in vietnam: Extending the tam model with trust and enjoyment. *Cogent Business & Management,* 8(1), 1891661.

Tran Le Na, N., & Hien, N. N. (2021). A study of user's m-wallet usage behavior: The role of long-term orientation and perceived value. *Cogent Business & Management,* 8(1), 1899468.

Tripathi, S. N., Srivastava, S., & Vishnani, S. (2022). Mobile wallets: achieving intention to recommend by brick and mortar retailers. *Journal of Marketing Theory and Practice,* 30(2), 240-256.

Türkmen, C., & Değerli, A. (2015). Transformation of consumption perceptions: A Survey on innovative trends in Banking. *Procedia-Social and Behavioral Sciences,* 195, 376-382.

Vallandingham, L. R., Yu, Q., Sharma, N., Strandhagen, J. W., & Strandhagen, J. O. (2018). Grocery retail supply chain planning and control: Impact of consumer trends and enabling technologies. *IFAC-PapersOnLine*, 51(11), 612-617.

Van Geest, M., Tekinerdogan, B., & Catal, C. (2021). Design of a reference architecture for developing smart warehouses in industry 4.0. *Computers in Industry*, 124, 103343.

Vasantha, S., & Sarika, P. (2019). Empirical analysis of demographic factors affecting intention to use mobile wallet. *International Journal of Engineering and Advanced Technology*, 8(6), 768-776.

Venkatesh, S., Thong, J. Y., & Xu, X. (2016). Factors Affecting Online Shopping Behavior: An Empirical Investigation. *International Journal of Human-Computer Studies*, 98, 1-17.

Venkatesh, V., & Bala, H. (2008). Technology Acceptance Model 3 and a research agenda on interventions. *Decision Sciences*, 39(2), 273-315.

Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the Technology Acceptance Model: Four longitudinal field studies. *Management Science*, 46(2), 186-204.

Venkatesh, V., & Morris, M. G. (2000). Why don't men ever stop to ask for directions? Gender, social influence, and their role in technology acceptance and usage behavior. *MIS Quarterly*, 24(1), 115-139.

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, 425-478.

Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *MIS Quarterly*, 36(1), 157-178.

Venkatesh, V., Thong, J. Y. L., & Xu, X. (2016). Unified theory of acceptance and use of technology: A synthesis and the road ahead. *Journal of the Association for Information Systems*, 17(5), 328-376.

Verma, N., & Singh, J. (2017). An intelligent approach to Big Data analytics for sustainable retail environment using Apriori-MapReduce framework. *Industrial Management & Data Systems*, 117(7), 1503-1520.

Videla-Cavieres, I. F., & Ríos, S. A. (2014). Extending market basket analysis with graph

mining techniques: A real case. *Expert Systems with Applications,* 41(4), 1928-1936.

Vidushi, V., & Kashyap, R. (2023). Reconfigure the apparel retail stores with interactive technologies. *Research Journal of Textile and Apparel,* 27 (1), 54-73.

Visa. (2017). *The future of commerce: Small business growth.* Retrieved from https://usa.visa.com/content/dam/VCOM/download/corporate/media/visa-future-of-commerce-report.pdf

Visa. (2019). *Visa back to business study.* Retrieved from https://usa.visa.com/dam/VCOM/global/support-legal/documents/visa-back-to-business-study-final.pdf

Vukovic, M., Lovrek, I., & Kraljevic, H. (2012). Discovering shoppers' journey in retail environment by using RFID. *Advances in Knowledge-Based and Intelligent Information and Engineering Systems,* 857-866. IOS Press.

Walczuch, R., Lemmink, J., & Streukens, S. (2007). The effect of service employees' technology readiness on technology acceptance. *Inf. Manag.*, 44, 206–215.

Wamba, S. F., Queiroz, M. M., Blome, C., & Sivarajah, U. (2021). Fostering financial inclusion in a developing country: predicting user acceptance of mobile wallets in cameroon. *Journal of Global Information Management (JGIM),* 29(4), 195-220.

Wang, D., Chen, Y., Chen, H., & Chen, X. (2018). Determinants of cloud computing adoption in e-commerce: A knowledge-based perspective. *Information & Management,* 55(3), 322-331.

Wang, J., Shen, X., Li, X., & Li, Y. (2019). Investigating the Factors Influencing Consumers' Behavioral Intention to Use the Mobile Payment: An Empirical Study of China's Young Consumers. *Journal of Retailing and Consumer Services,* 50, 246-262.

Wang, K., & Wang, Y. (2017, September). How AI affects the future predictive maintenance: a primer of deep learning. *International Workshop of Advanced Manufacturing and Automation,* 1-9. Springer, Singapore.

Wang, L., Wang, X., Sun, Y., & Du, Y. (2020). Adoption of mobile payment technology in retail: A case of China. *Journal of Retailing and Consumer Services,* 54, 102038.

Wang, Q., Zhu, X., Ni, Y., Gu, L., & Zhu, H. (2020). Blockchain for the IoT and industrial IoT: A review. *Internet of Things,* 10, 100081.

Wang, Y. S., & Shih, Y. W. (2009). Why do people use information kiosks? A validation of the Unified Theory of Acceptance and Use of Technology. *Government Information Quarterly*, 26(1), 158-165.

Wang, Y., Wang, Y., Liang, Y., & Huang, H. (2018). Investigating the effect of service quality, perceived value, and customer satisfaction on customer loyalty in mobile payment services. *Sustainability*, 10(6), 1994.

Webster, J., & Martocchio, J. J. (1992). Microcomputer playfulness: Development of a measure with workplace implications. *MIS Quarterly*, 16(2), 201-226.

Willems, K., Smolders, A., Brengman, M., Luyten, K., & Schöning, J. (2017). The path-to-purchase is paved with digital opportunities: An inventory of shopper-oriented retail technologies. *Technological Forecasting and Social Change*, 124, 228-242.

World Bank. (2019). *The Global Findex Database 2017: Measuring Financial Inclusion and the Fintech Revolution.* Retrieved from https://openknowledge.worldbank.org/bitstream/handle/10986/30498/9781464813315.pdf

World Bank. (2021). *World development report 2021: Data for better lives*. Retrieved from https://elibrary.worldbank.org/doi/abs/10.1596/978-1-4648-1600-0

Wu, H. C., Ai, C. H., & Cheng, C. C. (2019). Experiential quality, experiential psychological states and experiential outcomes in an unmanned convenience store. *Journal of Retailing and Consumer Services*, 51, 409-420.

Wu, J. H., Wang, Y. M., & Lin, L. M. (2019). Factors influencing purchase intention of green products: An extension of the technology acceptance model. *Journal of Cleaner Production*, 225, 444-454.

Wu, Y., & Wu, Y. (2020). Exploring Consumers' Intention to Use Mobile Apps in the Context of Social Commerce: A Perspective of the Stimulus-Organism-Response Model. *Journal of Retailing and Consumer Services*, 53, 101942.

Wünderlich, N. V., Heinonen, K., Ostrom, A. L., Patricio, L., Sousa, R., Voss, C., & Lemmink, J. G. (2015). "Futurizing" smart service: implications for service researchers and managers. *Journal of Services Marketing.*

Xu, X., Luo, Y., Pan, L., & Cai, Y. (2020). An empirical study of factors affecting customers' adoption of mobile payment services in China. *Journal of Business Research*, 117, 771-780.

Xu, Y., Shieh, C. H., van Esch, P., & Ling, I. L. (2020). AI customer service: Task complexity, problem-solving ability, and usage intention. *Australasian Marketing Journal (AMJ)*, 28(4), 189-199.

Yan, L. Y., Tan, G. W. H., Loh, X. M., Hew, J. J., & Ooi, K. B. (2021). QR code and mobile payment: The disruptive forces in retail. *Journal of Retailing and Consumer Services*, 58, 102300.

Yang, Z., & Ngo, Q. V. (2023). Consumer trust and repurchase intention in B2C e-commerce: a moderation model. *European Journal of International Management*, 19(2), 243-264.

Yegen, B., Kandır, S., & Büyüközkan, G. (2019). Predicting peer-to-peer lending default using machine learning algorithms: Evidence from a Turkish P2P lending platform. *Expert Systems with Applications*, 120, 117-127.

Yu, X., Fang, Y., & Kuo, P.-J. (2018). The effect of social media on online purchase intention: The mediating role of perceived trust and perceived value. *Journal of Electronic Commerce Research*, 19(4), 273-291.

Zhang, T., Liu, Y., Li, L., & Wang, W. (2019). The adoption of omnichannel retailing: The role of UTAUT2 and experience. *Journal of Business Research*, 98, 378-386.

Zhang, Z., Wang, X., Zhu, X., Cao, Q., & Tao, F. (2019). Cloud manufacturing paradigm with ubiquitous robotic system for product customization. *Robotics and Computer-Integrated Manufacturing*, 60, 12-22.

Zhou, M., Zhao, L., Kong, N., Campy, K. S., Qu, S., & Wang, S. (2019). Factors influencing behavior intentions to telehealth by Chinese elderly: An extended TAM model. *International Journal of Medical Informatics*, 126, 118-127.

Zhou, T., Lu, Y., & Wang, B. (2010). Integrating TTF and UTAUT to explain mobile banking user adoption. *Computers in Human Behavior*, 26(4), 760-767.

Zhou, T., Lu, Y., & Wang, B. (2017). Factors Influencing Mobile Commerce Adoption: A Meta-analysis and Modified Model. *Electronic Commerce Research and Applications*, 25, 16-29.

APPENDIX

Appendix 1 Measurement Items of the Survey.

Survey Questions	Constructs
1. When I use my mobile wallet, the waiting time for the transaction is short.	TS1
2. I believe that using mobile payment with QR code increases transaction speed.	TS2
3. Using mobile payment with QR code helps me reduce time spent shopping.	TS3
4. Using technology helps me control my daily life.	OP1
5. Products and services that use the latest technologies, such as mobile wallets, are much more useful.	OP2
6. New retail technology like mobile wallets helps me manage my purchases efficiently and effectively.	OP3
7. I like to try new retail technology.	INV1
8. When new technology emerges in my circle of friends, I am one of the first to try it.	INV2
9. I follow the latest trends in technology in the retail field.	INV3
10. I feel embarrassed when I have a problem with a high-tech gadget while people are watching.	DIS1
11. If other people know more about shopping technology than I do, I feel they have an advantage over me.	DIS2
12. I think mobile wallets are not designed to be easily understood by anyone.	DIS3
13. I think that mobile wallets offer a secure shopping experience with the necessary competencies.	TR1
14. I feel safe when saving my credit card information on my mobile phone.	TR2
15. I feel safe in my transactions with my mobile wallet defined phone.	TR3
16. Mobile wallets are useful for shopping.	PU1
17. Using mobile payment with QR code simplifies payment transactions.	PU2
18. I find it convenient to do grocery shopping with my mobile device than other methods.	PU3
19. I find it fun to shop with my mobile wallet.	PE1
20. The shopping process is enjoyable with my mobile wallet.	PE2
21. I am having fun using my mobile wallet.	PE3
22. The use of the mobile wallet is straightforward and clear.	PEU1
23. In general, I think shopping with a mobile wallet is simple.	PEU2

Appendix 1 (Continued) Measurement Items of the Survey.

Survey Questions	Constructs
24. Learning how to use my mobile wallet was easy.	PEU3
25. All things considered, using mobile wallet technology is a good idea.	AT1
26. I find it positive to shop with a mobile wallet.	AT2
27. I recommend other people to use mobile wallet app as well.	AT3
28. I plan to increase the use of mobile wallets in the future.	IU1
29. I want to use QR code mobile payment instead of traditional payment methods when purchasing.	IU2
30. I will often use my mobile wallet.	IU3

Appendix 2 Profile of the Participant.

Participant's Profile	
Participant's Age	
Participant's Gender	
Participant's Education Information	
Participant's Mobile Wallet Time of Use	

RESUME

EDUCATION INFORMATION

2016- 2023: Marmara University Engineering Management (Ph.D)

- Thesis: An Analysis of Customer Attitudes towards Technology-Driven Products: A Case Study in the Retail Industry

2013- 2016: Marmara University Industrial Engineering (Master of Science)

- Thesis: Competitive Position Analysis of the Airline Industry

2014-2015: Universitad Politecnico de Catalunya-ETSEIB Barcelona Industrial Engineering (Erasmus Student)

2009-2013: Isık University Industrial Engineering (BSc)

WORK EXPERIENCE

2022 March –(Continue): Yıldız Holding, Project & Business Development Manager

2021 January – 2022 March: Migros, Business Development & Partnership Executive

2019 July – 2021 January: Migros, Senior Business Development & Partnership Specialist

2019 February – 2019 July: Çimsa, Supply Chain Business Development Specialist

2017 September – 2019 February: Eczacıbaşı Monrol, Junior Project Specialist

2016 March – 2017: September: Uskudar University, Research Assistant

PUBLISHED ARTICLES

Hopalı, E., Vayvay, Ö., Kalender, Z. T., Turhan, D., & Aysuna, C. (2022). How Do Mobile Wallets Improve Sustainability in Payment Services? A Comprehensive Literature Review. *Sustainability*, *14*(24), 16541.

Hopalı E. & Çakmak A. (2020): "Prediction of Daily CO2 Emissions of a Factory Using ARIMA and Holt-Winters Seasonal Methods" *International Journal of Information, Business and Management 12 (3),* 51-62.

Hopalı E. & Vayvay Ö. (2018): "Industry 4.0 as the last industrial revolution and its opportunities for developing countries" *Analyzing the Impacts of Industry 4.0 in Modern Business Environments*, 65-80 (Book Chapter).

Hopalı E. & Vayvay Ö. (2018): "Internet of Things (IoT) and its Challenges for Usability in Developing Countries" *International Journal of Innovation Engineering and Science Research 1 (2),* 6-9.

Donmez CÇ., Hopalı E. & Hamal S. (2017): "Endüstri Sektörlerinin Ekonofizik Açıdan Kümelenme Analizi: Türkiye Uygulaması" *Electronic Journal of Social Sciences 16 (63),* 1081-1091.