IBN HALDUN UNIVERSITY
SCHOOL OF GRADUATE STUDIES
DEPARTMENT OF MANAGEMENT

PH.D. THESIS

FACTORS AFFECTING USER BEHAVIORAL INTENTION TO ADOPT SELF-SERVICE KIOSKS IN AIRPORTS: A STRUCTURAL EQUATION MODELING (SEM) APPROACH

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THESIS SUPERVISOR
PROF. ALİ OSMAN KUŞAKCI

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by

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A thesis submitted to the School of Graduate Studies in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Management

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ISTANBUL, 2024

APPROVAL PAGE

This is to certify that we have read this thesis and that in our opinion it is fully adequate, in scope and quality, as a thesis for the degree of Doctor of Philosophy in Management.

Thesis Jury Members

Title - Name Surname	Opinion	Signature

This is to confirm that this thesis complies with all the standards set by the School of Graduate Studies of Ibn Haldun University.

Date of Submission

Seal/Signature

ACADEMIC HONESTY ATTESTATION

I hereby declare that all information in this document has been obtained and presented in accordance with academic rules and ethical conduct. I also declare that, as required by these rules and conduct, I have fully cited and referenced all material and results that are not original to this work.

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Signature:

ÖZ

HAVALIMANLARINDA SELF SERVIS KIOSKLARI KULLANMAYA YÖNELIK KULLANICI DAVRANIŞSAL NIYETINI ETKILEYEN FAKTÖRLER: YAPISAL EŞITLIK MODELLEMESI (SEM) YAKLAŞIMI

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Modern havalimanları, verimliliği ve yolcu deneyimini artırmak için yolcu self servis teknolojilerine (SST'ler) doğru ciddi bir yönelimimerkeze alan dijital bir dönüşümden geçiyor. SST'lerin önemli bir örneği tüm havalimanı paydaşlarına gözle görülür faydalar sağlama potansiyeline sahip olan Self-check-in kiosk'lar (SCK'lar)'dır. Fakat, yolcuların SCK'ları benimsemesi benzer teknolojilere kıyasla nispeten yavaştır. Daha otesi, yolcuların SCK'ları benimsemesini etkileyen faktörleri yapılan araştırmalar sınırlı kalmaktadır. Bu çalışma, yolcuların SCK'ları kullanma davranışsal niyetlerini etkileyen belirleyici faktörleri inceleyen yeni bir model önererek bu boşluğu kapatmayı amaçlamaktadır. Bu çalışma, yolcuların SCK'ları kullanımına yönelik davranışsal niyetinin belirleyici faktörlerini incelemek için UTAUT2 ve SSTQUAL modellerini entegre ederek bu boşluğu kapatmayı amaçlamaktadır. Önerilen model, teknoloji kabulü için en popüler modellerden birini (UTAUT2) ve SST'lerin kalite yönünü değerlendirmek için özel olarak tasarlanmış bir ölçekle (SSTQUAL) entegre etmiştir. Önerilen model, beş UTAUT2 bileşenini (performans beklentisi, çaba beklentisi, sosyal etki, kolaylaştırıcı koşullar ve hedonik motivasyon) ve dört SSTQUAL bileşenini (işlevsellik, güvence, emniyet ve zevk) kapsamaktadır. Ek olarak, algılanan riskin davranışsal niyet ile gerçek SCK kullanımı arasındaki ilişki üzerindeki düzenleyici etkisi araştırılmıştır. Veriler, Türkiye, İstanbul'daki iki büyük havalimanında anketler yoluyla 380 yolcudan toplanmıştır. Araştırma hipotezlerini test etmek için yapısal eşitlik modellemesi kullanılmıştır. Sonuçlar, performans beklentisi, sosyal etki, işlevsellik ve eğlencenin SCK'ları kullanmaya yönelik davranışsal niyeti olumlu yönde etkilediğini göstermektedir. Dahası, algılanan riskin davranışsal niyet ile SCK kullanımı arasındaki ilişki üzerinde olumsuz bir düzenleyici etkiye sahip olduğu bulunmuştur. Bu çalışma, yolcular tarafından SCK'ların benimsenmesinin anlaşılmasına katkıda bulunmakta ve havalimanı yöneticilerinin SCK uygulamasını ve kullanımını optimize etmeleri için değerli içgörüler sunmaktadır.

Anahtar Kelimeler: Havalimanı, Kiosk, Self Servis Teknolojisi, SSTQUAL, Teknoloji Kabulü, Teknoloji Kabul ve Kullanım Birleştirilmiş Teorisi.

ABSTRACT

FACTORS AFFECTING USER BEHAVIORAL INTENTION TO ADOPT SELF-SERVICE KIOSKS IN AIRPORTS: A STRUCTURAL EQUATION MODELING (SEM) APPROACH

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August 2024, 142 Pages

Modern airports are undergoing a digital transformation characterized by a shift towards passenger self-service technologies (SSTs) to enhance efficiency and passenger experience. Self-check-in kiosks (SCKs) are a prominent example of SSTs with the potential to benefit all airport stakeholders. However, the adaptation of SCKs by passengers is relatively slow compared to similar technologies. In addition, research on investigating factors influencing passenger adoption of SCKs remains limited. As a result, this study aims to bridge this gap by proposing a novel model that examines the determinants factors that influence passengers' behavioral intention to use SCKs. The proposed model integrates one of the most popular technology acceptance models (UTAUT2) with an SSTQUAL scale, which is specially designed to evaluate the quality aspect of SSTs. The proposed model encompasses five constructs from the UTAUT2 model (performance expectancy, effort expectancy, social influence, facilitating conditions, and hedonic motivation) and four constructs from the SSTQUAL scale (functionality, assurance, security, and enjoyment). Additionally, the moderating effect of perceived risk on the relationship between behavioral intention and actual SCK usage was investigated. Data were collected from 380 passengers through surveys at two major airports in Istanbul, Türkiye. Structural equation modeling (SEM) was employed to test the research hypotheses. The results of SEM analysis indicate that performance expectancy, social influence, functionality, and enjoyment positively influence behavioral intention to use SCKs. Moreover, perceived risk was found to have a negative moderating effect on the relationship between behavioral intention and SCK usage. This study contributes to the understanding of SCK adoption by passengers and provides valuable insights for airport managers to optimize SCK implementation and usage.

Keywords: Airport, Kiosk, Self-service Technology, SSTQUAL, Technology Acceptance, Unified Theory of Acceptance and Use of Technology.

DEDICATION

I humbly dedicate this dissertation to the innocent children who lost their lives due to war crimes committed in Gaza...

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First and foremost, I want to thank Allah the Almighty for illuminating my heart and showing me the path.

I would like to start by expressing my deepest gratitude to my family. To my beautiful wife, Bahar, the true spring of my life, I express my heartfelt thanks for her infinite support and unconditional love. I am also profoundly grateful to my parents: my father, Mesut, for always being there for me, and my mother, Melike, my caring angel. None of these achievements would have been possible without you. I also extend my thanks to my brother, Milad, for his guidance and to his wonderful wife, Deniz, for joining our family and bringing Pamir into our lives.

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF SYMBOLS AND ABBREVIATIONS

SST	Self-Service Technology
UTAUT	Unified Theory of Acceptance and Use of Technology
IGA	Istanbul Grand Airport
ISG	Istanbul Sabiha Gökçen International Airport
SSTQUAL	Self-Service Technology Service Quality
SEM	Structural Equation Modeling
SCK	Self-Check-in Kiosk
CAGR	Compound Annual Growth Rate
BI	Behavioral Intention
ICAO	International Civil Aviation Organization
RPK	Revenue Passenger-Kilometers
TBSS	Technology-Based Self-Service
IS	Information Systems
HCI	Human-Computer Interaction
UAV	Unmanned Aerial Vehicles
ATM	Automated Teller Machines
EE	Effort Expectancy
PE	Performance Expectancy
HM	Hedonic Motivation
SI	Social Influence
FC	Facilitating Condition
BI	Behavioral Intention
UB	Use Behaviour
FU	Functionality
ASU	Assurance
ENJ	Enjoyment
SEC	Security
PR	Perceived Risk
TAM	Technology Acceptance Model

CHAPTER I

INTRODUCTION

This chapter provides a general background on the significance of self-service technologies specifically for airports and air travel. Moreover, it illustrates the current market status and its future direction based on the available market analysis reports. Next, it explains the existing research gap and discusses the dissertation problem statement. It then briefly demonstrates the research questions that this study aims to answer. Finally, the chapter ends by highlighting the significance of this study and its potential contributions.

1.1. Study Background

The rise of advanced technologies has fundamentally reshaped traditional business process patterns. Organizations are now unlocking new levels of efficiency by strategically integrating new technologies into their workflows. Consequently, technology has created new ways of creating customer values, communication, and collaboration between business and their customers (Michelini & Fiorentino, 2012; Porter & Kramer, 2011). Self-service technology (SST) is one such technology that enables customers to benefit from companies' respective products and services independently, as they desire (Ford et al., 2001). In simple words, SSTs attempt to provide companies' promised services to their customers without needing employee-customer interaction.

The rapid accessibility of technology, exemplified by the widespread adoption of smartphones, has resulted in a remarkable rise in the use of SSTs over the past decades. This growth is driven by the convergence of consumer demand for convenience and control alongside advancements in user-friendly interfaces that have broadened accessibility (Chan & Petrikat, 2022). A market analysis report conducted by Grand View Research in 2020 illustrated that the global self-service technology market size was valued at $34.03 billion in 2022 and is expected to grow at a compound annual growth rate (CAGR) of 13.8% by 2027 (Figure 1.1.). According to the report, the industries that benefited the most from SSTs were travel and tourism, retail, and banking (Grand View Research, 2020).

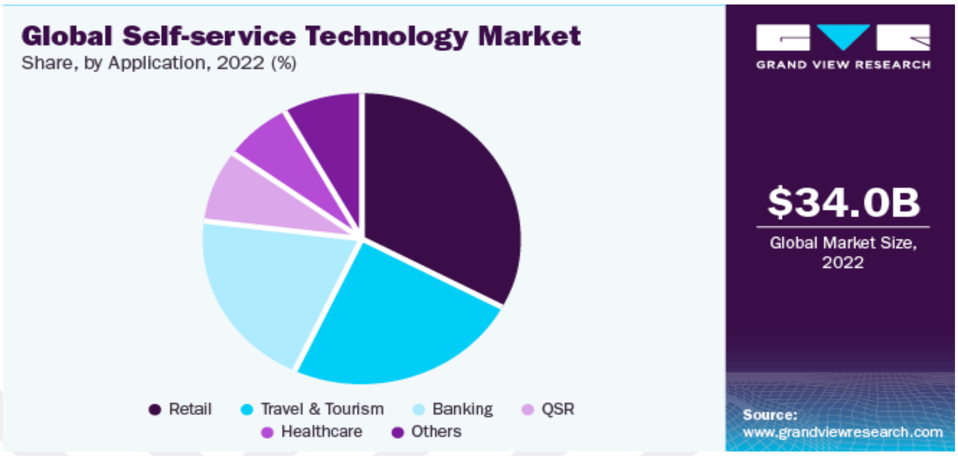

Figure 1.1. Global Market Size of SST by Application

Source: Grand View Research, 2020

A similar figure was projected by another market analysis (Dhapte, 2024), which estimated that the market size of SSTs would grow from 36.6 billion dollars in 2024 to more than 76 billion dollars by 2032, demonstrating a 10.10 percent CAGR growth in the forecasted period (Figure 1.2)

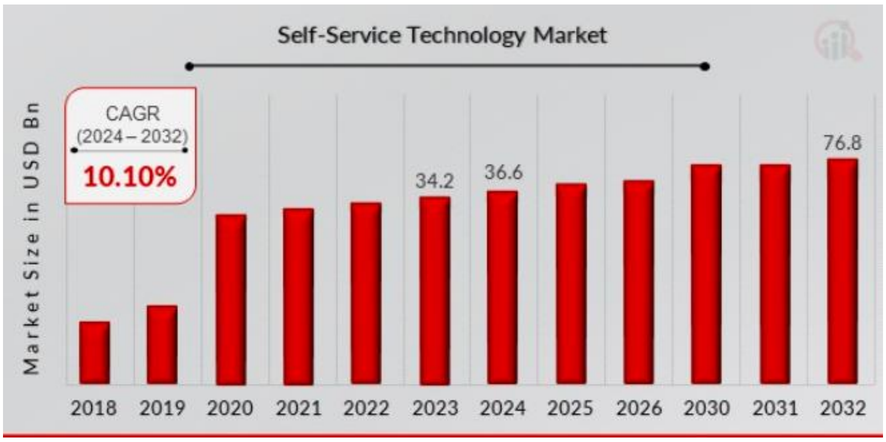

Figure 1.2. The SST Market Size

Source: https://www.marketresearchfuture.com/

Many studies show the proven benefits of SSTs in many aspects, such as gaining competitive advantages, higher efficiency, and enhanced financial performance (Beatson et al., 2007; Chan & Petrikat, 2022). Figure 1.3 shows that businesses with self-service initiatives had a 3.5% increase in customer satisfaction compared to businesses without such programs (Chan & Petrikat, 2022).

Figure 1.3. Comparison of Companies with and without SSTs

Source: Chan & Petrikat, 2022

Airports are bustling hubs that cater to millions of people. With the constant rise in air travel, the need for efficient and seamless passenger processing has become paramount. In addition, airports have the potential for significant improvements in their operations by adopting SSTs (Ku & Chen, 2013). Digital transformation has revolutionized the air travel industry, from mobile check-in apps to interactive digital displays. Nowadays, modern airports provide passengers with various forms of SSTs, such as online and kiosk check-in, self-service bag drop kiosks, automated security screening, automated border and passport control, and many more (Shady G. Abdelaziz, 2010). Adopting these technologies has proven various benefits, such as cost reduction (Meuter et al., 2000b), enhanced performance (Kim et al., 2019), and improved passenger travel experience and loyalty (Drennen, 2011). Moreover, crises such as the COVID-19 pandemic and the 2023 summer staff strikes in Europe (Fox, 2023; Shabani, 2023), which caused severe disruption to summer travel in 2022, once again revealed the significance of SST for the aviation industry (Meidute-Kavaliauskiene et al., 2021).

One of the most well-known types of SSTs is self-service kiosks. A self-service kiosk is an interactive touchscreen computer/tablet that allows users to access information or their desired services independently, meaning they do not need the assistance of an organization's employee (Rastegar, 2018).

In the case of airports, interactive kiosks may appear as self-check-in kiosks (SCKs) to empower passengers' check-in process. These kiosks can become crucial equipment for airports. They are designed to help passengers check-in quickly and easily, reduce airline and airport costs, and save space for airports (Drennen, 2011). Consequently, the implementation of self-check-in kiosks in airports has led to a noticeable reduction in waiting times, resulting in a more seamless and stress-free travel experience for passengers (Sabatová et al., 2016).

Like SSTs, the demand for adaptation of SCKs in airports is increasing rapidly. The market size for airport kiosks is estimated at 2.36 billion dollars in 2024, and it is expected to reach 3.60 billion dollars by 2029, growing by 8.78% CAGR (*Moderator Intelligence Research*, 2024) (Figure 1.4.)

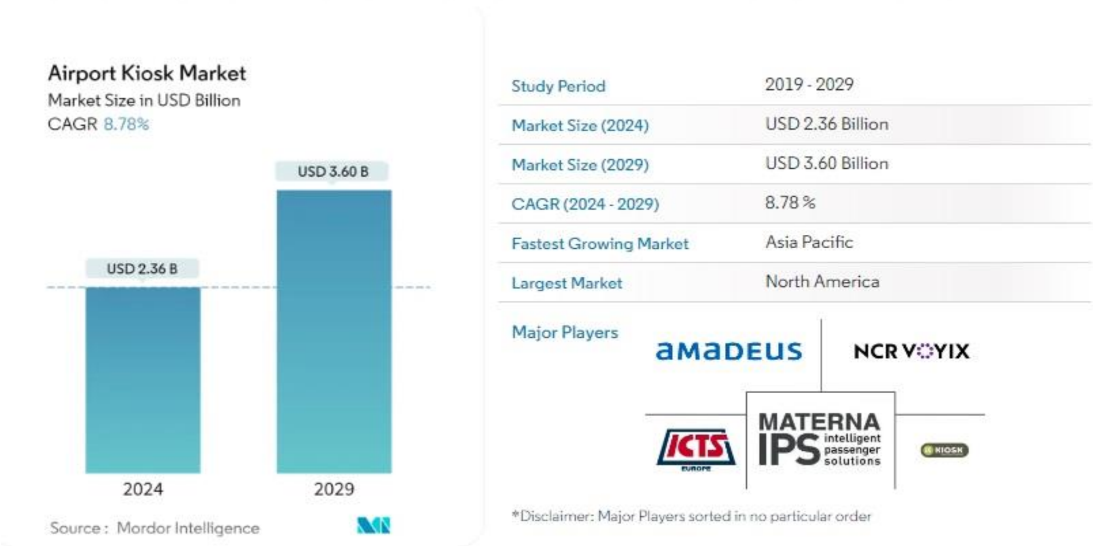

Figure 1.4. Airport Kiosk Market Analysis

Source: https://www.mordorintelligence.com/

Long queues at check-in counters have long been a source of frustration for travelers. Self-check-in kiosks provide a practical solution to this issue. Besides a faster and easier check-in process, SCKs can enhance the travel experience for passengers by providing features such as seat selection, frequent flyer status updates, and accessing boarding passes independently (Chang & Yang, 2008).

In addition, self-check-in kiosks empower passengers by providing them with greater control and convenience over their travel arrangements. With user-friendly interfaces and multilingual options, these kiosks accommodate travelers of diverse backgrounds, ensuring accessibility for all. Moreover, clear instructions and visual prompts guide passengers with language barriers through their self-check-in process. This level of autonomy not only enhances the overall passenger experience but also fosters a sense of satisfaction and independence (Djelassi et al., 2018). Moreover, the implementation of self-check-in kiosks enables airports to optimize resource allocation. By automating routine tasks, airports can allocate personnel to other critical areas such as security, immigration, and customer service (Chan & Petrikat, 2022). Such strategic deployment of staff enhances the overall efficiency and effectiveness of airport operations, ensuring a smoother flow of passengers through the terminal.

1.2. Research Gap

Despite their functionality and popularity, it seems that passengers' acceptance and adaptation of self-check-in kiosks in airports is slower with respect to other industries, such as banking or retail (Dhapte, 2024). Although this can be explained by the technological maturity of kiosks among different industries, it appears that some overlooked factors may exist that contribute to the behavioral intention of passengers toward SCKs. In addition, evidence suggests that regional variations in passengers can also be a contributing factor (Bogicevic et al., 2017; Khairat, 2014; Kuo & Jou, 2018). This raises the attention toward factors affecting passengers' acceptance or rejection of self-service technologies in airports in different regions with unique passenger profiles.

A review of the literature reveals that the topic of SSTs has been studied from various perspectives in the airport industry. Most previous studies focused on the characteristics of SSTs and their effects on passengers’ perceived value, satisfaction, and travel experience (Antwi et al., 2021; Bogicevic et al., 2017; Deel, 2010; Djelassi et al., 2018; Kilic, 2019; Kim et al., 2019). However, when it comes to passengers' behavioral intention (BI) toward SSTs, most scholars studied BI through the lens of satisfaction (Kim & Park, 2019b; Lu et al., 2009b; Taufik & Hanafiah, 2019; Wittmer, 2011). Furthermore, studies that attempt to investigate factors affecting BI toward SSTs independently mainly focused only on two core dimensions: usefulness and ease of use (Coeckelbergh, 2012; Momani et al., 2017; Momani & Jamous, 2017). Studies of SSTs for other industries suggest that other dimensions, such as social influence, enjoyment, individual competence, and perceived risks, may also contribute to the BI of customers toward SSTs (L. Da Chen & Tan, 2004; Chiu et al., 2009; J. Lee & Allaway, 2002; Malanga et al., 2022). Given the evidence presented, it is reasonable to assume that other factors such as the assurance and technology proficiency of passengers, privacy and security concerns, and technical malfunctions, may significantly contribute to the effect of the BI of passengers toward self-check-in kiosks.

Previous research investigating solely passenger BI towards SCKs has primarily relied on variations of the Technology Acceptance Model (TAM) (Lu et al., 2009; Taufik & Hanafiah, 2019). While TAM remains a well-established framework, its status as one of the oldest available models necessitates consideration of more recent theoretical advancements that may offer a more comprehensive understanding of passenger adoption. Furthermore, the TAM is not specifically tailored to capture the unique perspective of customers. TAM offers a more general framework applicable to various user types, such as organizational employees, managers, or consumers (Coeckelbergh, 2012; Momani et al., 2017).

Another critical limitation of existing research on self-service applications lies in the treatment of self-service kiosks. Most prior studies group kiosks under the broader umbrella of SSTs, failing to acknowledge their distinct characteristics. This approach overlooks the unique functionalities and user interactions that kiosks offer compared to other SSTs. It is essential to establish a separate conceptual branch of research specifically focused on interactive self-service kiosks to gain a deeper understanding of passenger adoption and optimize kiosks (Vakulenko et al., 2018).

1.3. Research Questions and Objectives

In order to comprehensively address all the gaps stated above, this dissertation proposes a novel approach to explore all significant factors that contribute to shaping passengers’ behavioral intention to use self-check-in kiosks in airports. This research proposes a novel model that integrates two well-regarded, yet relatively recent, approaches: The Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) developed by (Venkatesh, Thong, & Xin Xu, 2012) and the Self-Service Technology Service Quality (SSTQUAL) scale developed by Lin & Hsieh (2011). Moreover, the moderating effect of perceived risk on the behavioral intention of passengers was also added to the model. The proposed model aims to understand significant factors affecting passengers' behavioral intention to adopt SCKs at the Istanbul Grand Airport (IGA) and Istanbul Sabiha Gökçen (ISG) Airport, two major airports in Istanbul, Turkey. The research utilizes Structural Equation Modeling (SEM) to analyze data collected through surveys randomly distributed at designated airports. IBM SPSS or SmartPLS 4 software will be employed to conduct the factor and path analysis.

Accordingly, the following research questions are developed for this study:

i. What are the determinant factors that significantly affect the behavioral intention of passengers toward using self-service kiosks in airports?
ii. Is there any moderating effect of perceived risk on the behavioral intentions of passengers for using SCKs?
iii. What is the significance of passengers' characteristics (gender, age, education, travel purpose, etc.) on the behavioral intention of passengers toward SCKs?

1.4. Significance of the Study

To situate this research within the existing literature, a systematic literature review conducted by Vakulenko et al. (2018) will serve as a key reference point. Their study comprehensively examined customer value in the context of self-service kiosks by analyzing 76 relevant articles. According to Vakulenko et al. (2018), theories used in previous studies can be categorized into three groups; technology-oriented theories, customer-oriented theories, and service-oriented theories. The biggest category comprises studies that use technology-oriented theories to explore SST, its application, or technological innovations. This dissertation will also fall into this category. However, the distinguishing point for this thesis is the combination of UTAUA (technology-oriented theory) with SSTQUAL (service-oriented theory). According to Vakulenko et al. (2018), only three articles used a combination of theoretical backgrounds in previous studies. Moreover, this approach, a combination of the technology adaptation models with quality scales, is gaining popularity and is strongly suggested in recent studies (Malanga et al., 2022).

In their study, Vakulenko et al. (2018) created an inventory of customer values based on previous studies. According to the extracted value elements from the customers' perspective, three progressive stages were created: pre-experience, kiosk interaction, and post-experience. Since this thesis will focus on the behavioral intention of passengers, it will stand in the post-experience category. It is noteworthy that previous research has paid relatively scant attention to the pre-experience and post-experience stages in user adoption of self-service kiosks (Vakulenko et al., 2018). This study further distinguishes from previous studies by investigating perceived risk as a moderator variable influencing passengers' behavioral intention to utilize self-service check-in kiosks.

Another uniqueness of this thesis arises from the geographic location where the study will be conducted. According to Vakulenko et al. (2018), the geographical distribution of the published studies on interactive kiosks is mainly in the United States, Europe, and Asia. This research aims to contribute to the limited body of scholarship on technology acceptance in the Turkish airport context. By investigating passenger perceptions of SCKs, this study has the potential to be among the pioneering works examining kiosk adoption within the Turkish aviation industry. The significance of this issue arises from considering the prominent role of Turkish civil aviation in the world. According to the latest data released before the COVID-19 pandemic by the International Civil Aviation Organization (ICAO), Türkiye ranks 12th worldwide by Revenue Passenger-Kilometers (RPK) and 11th by Revenue Ton-Kilometers on scheduled services (Zaimoglu, 2018). Furthermore, Türkiye’s airports hosted about 210 million passengers in 2018, with domestic passengers increasing by 3% and international passengers increasing by 16% over 2017. After the COVID-19 pandemic, Turkey returned to pre-pandemic air passenger numbers in 2023, surpassing a total of 214.23 million passengers. It is anticipated that these numbers to exceed 140 million passengers by 2025 (Yildiz Unal, 2024). In addition, Istanbul Grand Airport (IGA), one of the selected airports in this study, is known as the most significant international airport in the world. Despite only opening its operations just before the COVID pandemic in 2019, IGA quickly became Europe's second-busiest passenger hub. It served 76 million passengers in 2023, following closely behind London Heathrow's annual total of 79.2 million travelers. The airport targets 85 million passengers by the end of 2024 (Gill, 2024).

CHAPTER II

LITERATURE REVIEW ON DIGITALIZATION IN AIRPORTS

This chapter presents a scoping review that was conducted prior to this dissertation. The conducted scoping review aimed to identify, categorize, and discuss topics that had investigated applications of artificial intelligence (AI) in airports. The aim was to identify the existing gaps and discuss the potential direction of future research in this context. In fact, based on the findings and discussion from this scoping review, the researcher was able to focus on selecting a dissertation topic that aligns with the current potential and needs of the airports and passengers.

2.1. Digitalization in Airports

Since the start of the COVID-19 pandemic, experts and scholars in the aviation industry have emphasized on a crucial point, and that is the need for airports to become more flexible and smarter to face the challenges ahead. In recent years, the airport industry has undergone a profound transformation fueled by artificial intelligence (AI). As airports worldwide deal with increasing passenger volumes, growing security concerns, and the demand for enhanced efficiency, the imperative for innovative solutions has never been more crucial. In this context, AI offers a transformative potential, revolutionizing various aspects of airport management, from passenger experience and security screening to baggage handling and air traffic control (Alam et al., 2024; Dožić, 2019; X. Du et al., 2020; Tang et al., 2022). With the help of AI-driven technologies, airports can streamline operations, optimize resource allocation, and minimize disruptions, which ultimately enhance safety, efficiency, and overall passenger satisfaction (Bogicevic et al., 2017). More importantly, with the advancement of AI, its applications in airports will continue to evolve, and there will be numerous and surprising developments in more aspects.

Scholars across diverse disciplines study the application of AI more each day, and the aviation industry is no exception. This growing interest necessitates the development of comprehensive systematic review papers to understand the current research landscape and future directions. However, a critical gap exists in the research on AI applications within the aviation sector, calling for a comprehensive meta-analysis of the literature. While the potential of AI in aviation is widely acknowledged in the literature, surprisingly, systematic analysis of the existing papers and identification of future research directions is currently lacking. The current landscape of papers identifying the main concepts for AI applications in the aviation sector is extremely limited. Beyond a handful of conference papers, the number of existing research articles within this domain scarcely surpasses five (H. Huang & Zhu, 2021; Sadou & Njoya, 2023; Tang et al., 2022; Zaoui et al., 2024). Even within this restricted body of literature, existing studies either adopt a narrow approach, reviewing solely specific papers for particular applications of AI in airports, or, conversely, take an overly broad perspective, offering minimal contributions to the conceptualization of the topic.

To date, only two reviews have explored the topic of AI for the aviation industry, yet neither review explicitly explored AI's applications in airports. Zaoui et al. (2024) recently conducted an industry-wide review through the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) protocol for the impact of AI on the aeronautic industry (Zaoui et al., 2024). Similarly, Sadou and Njoya (2023) conducted a bibliometric and systematic literature review for applications of AI in the air transport industry (Sadou & Njoya, 2023). The remaining literature consists of conference papers or studies with a narrow focus on the use of artificial intelligence for specific applications for airports, such as Air Traffic Management (Tang et al., 2022) or IoT for smart airports (H. Huang & Zhu, 2021).

This scarcity presents a significant barrier to understanding the current state of knowledge for the application of AI in airports, hindering the identification of key research trends and the formulation of focused research agendas. This study aims to address this gap by conducting a comprehensive scoping review of AI applications and their potential impact on the airport industry. This paper maps and categorizes different AI applications for airport activities. In addition, It identifies areas that have received significant research attention and highlights those requiring further exploration, providing a comprehensive overview and valuable guidance for future research endeavors.

As a result, the following research questions were formulated for this scoping review: What are the known applications of AI in the literature for airports? In which areas of the airport these studies were conducted? And finally, what are the existing gaps and directions for future studies in this context? To address these questions, we conducted a scoping review to answer this question, focusing solely on peer-reviewed articles published in prominent databases up to date.

2.2. The Scoping Review

Scoping reviews are considered as one of the most popular methods for synthesizing research evidence (Pham et al., 2014). At its core, it offers a holistic overview of the current research landscape, providing a foundation for future investigations (Arksey & O'Malley, 2005). In short, a scoping review is a valuable tool for conducting meta-analysis and systematically mapping the existing literature on a specific topic, making it invaluable for researchers and practitioners (Munn et al., 2018).

There are various methods for conducting a scoping review (Kastner et al., 2012). The methodology selected for this scoping review is based on the framework outlined by Moher et al. (2015). They developed a protocol for conducting systematic reviews and meta-analyses called PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-analysis). This protocol is considered as one of the most reliable procedures for conducting a meta-analysis (Moher et al., 2015). Later, an extension of PRISMA (PRISMA-ScR) for scoping review was developed by Tricco et al. (2018). As a result, the following discussion follows the PRISMA-ScR checklist for enhancing its transparency and reliability.

2.2.1. Search Strategy

According to the PRISMA protocol, after identifying the desired topic and research question, relevant keywords need to be searched in the selected databases (Moher et al., 2015). The searches were conducted to identify relevant literature using the main keywords ‘artificial intelligence’, ‘AI’, and ‘airport.’ The search was conducted for the title, abstract, and keywords mentioned in the articles. In order to find the most relevant articles, the following subject areas were selected: engineering, computer science, social science, mathematics, business and management, environmental science, and decision science. A literature search was conducted through databases that index all fields, including Scopus and Web of Science (WOS). Although the topic of AI is a relatively new topic, we decided not to set a specific date range in the search in order to demonstrate how specific applications evolved over time.

2.2.2. Study Selection

The following criteria were considered when selecting articles: (i) the article discussed a method or application of AI that is related to any airport activities; (ii) the article used airports as a case study or airport dataset for demonstrating AI applications; (iii) the article was published in peer-reviewed journals; (iv) the language of the article was in English. Articles that did not meet the following criteria were removed: (i) the article did not directly discuss AI applications for airports (e.g., the paper commented on the potential or future use of AI in airports or reviewed other articles without contributing original research); (ii) used airports just as a crowded place without any specific application of AI for airports (iii) the full text of the article was not found or accessed.

In each article, we looked for (i) the research goals (i.e., what the study aimed to achieve), (ii) where in the airport AI was used (specific areas/department/tasks), (iii) the exact function and capabilities of the AI for airports, (iv) the authors' country of origin, (v) the academic discipline the research belonged to, and (vi) the year the article was published.

2.3. Result of Scoping Review

The PRISMA flowchart of this study is illustrated in Figure 2.1. The stated search strategy for this study initially identified 1221 items. After removing duplicates, 311 unique research articles remained for screening.

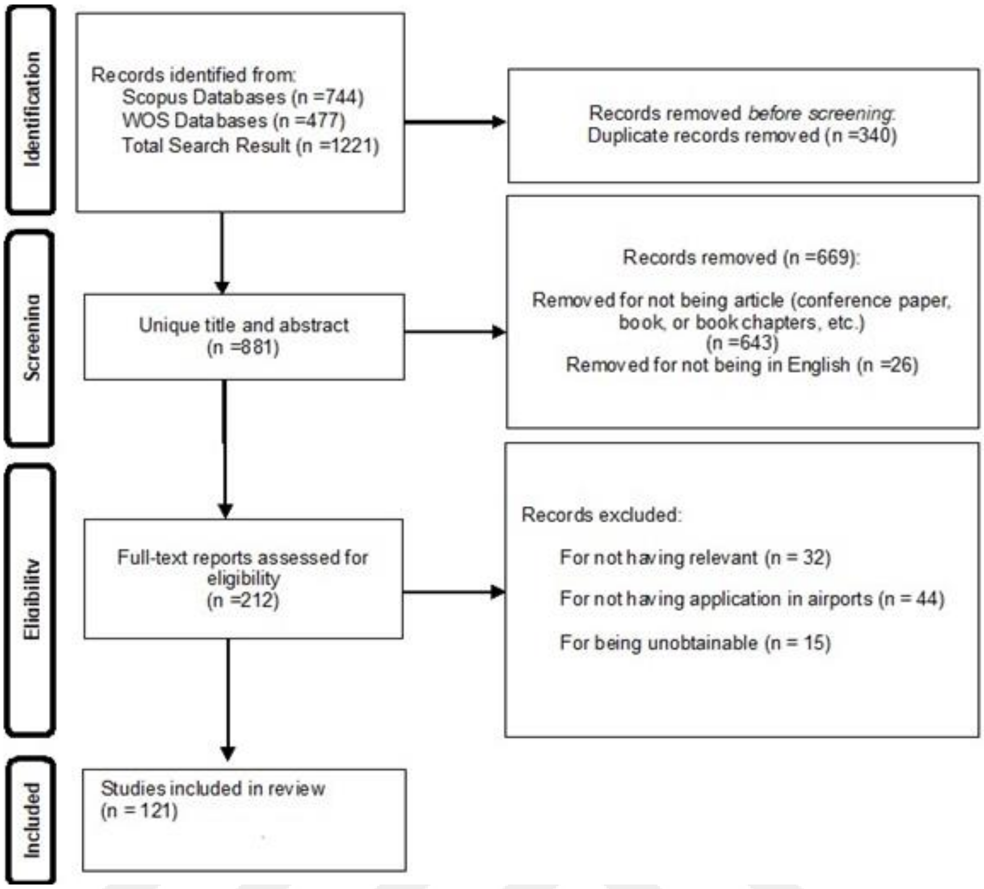

Figure 2.1. PRISMA Flow Chart for the Study

2.3.1. Characteristics of Articles

The 121 identified articles were published over a period of 30 years, and their publication rate has increased dramatically over the past four years. The span of publication years ranges from 1997 to 2023 (Figure 2.2.), with a mean publication year of 2016 (standard deviation 7.2). The median publication year was 2020, with the highest number of publications in 2023 (n=26). No time restrictions were applied in the search to cover all the topics studied to date. The pioneer studies for utilizing AI in airports were for tracking baggage (Yfantis, 1997) and scheduling gate allocation (Jo et al., 1997).

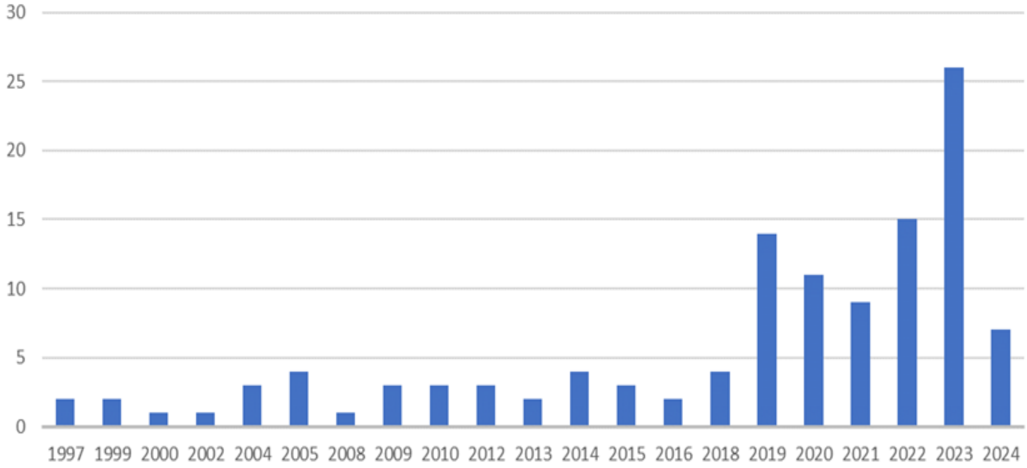

Figure 2.2. Published Articles by Years

The geographical distribution of included articles is illustrated in Figure 2.3. In total, 121 articles were distributed among 35 countries, with China and the United States as the leading countries, contributing 39 and 15 articles, respectively. Another dominant region is Europe, which contributed 32 published articles. The United Kingdom, Austria, and the Netherlands each published four articles, while Italy, Spain, Germany, the Russian Federation, and France each contributed three articles.

Figure 2.3. World-map Distributions of Contributing Countries

The majority of articles in the study belong to the fields of engineering (n=32) and computer sciences (n=28), comprising more than half of the included studies. The distribution of subject areas of the articles is illustrated in Figure 2.4.

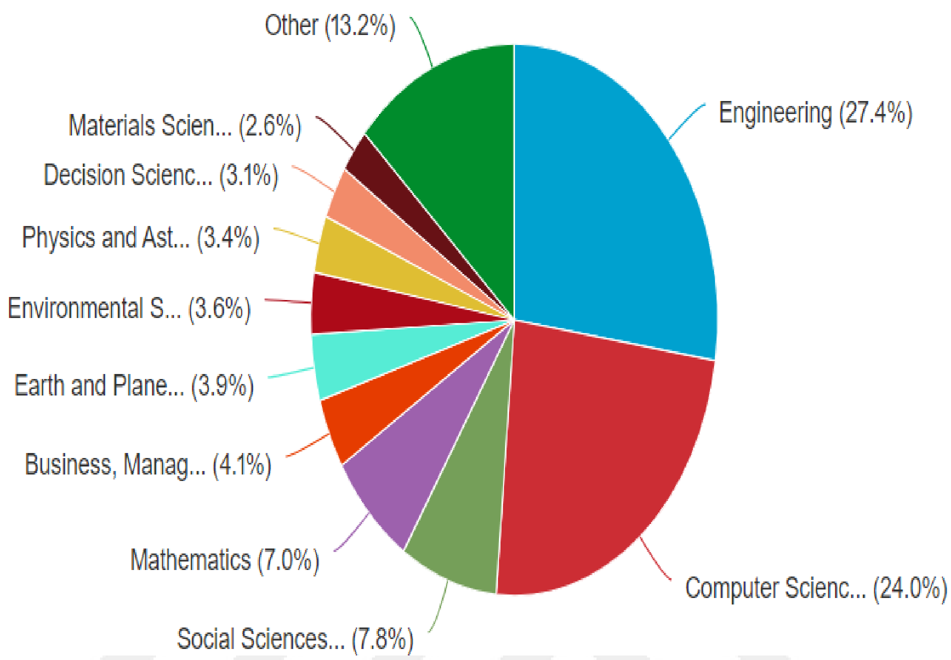

Figure 2.4. Subject Area of Included Articles

2.3.2. Field Application of AI in Airports

After analyzing 121 included articles, eight main topics were identified, each comprising various subcategories showcasing unique applications of AI for airports (Table 2.1). These main categories are as follows: Security, Management and Administration, Airport 4.0, Passengers, Air Traffic Control, Weather and Climate, and Safety. The most studied areas were Management and Administration (n=43) and Air Traffic Control (n=27), while the most minor topic was regarding Passengers (n=6). The rest of the topics were almost equally studied, including security (n=13), safety (n=14), Airport 4.0 (n=9), and Climate and weather (n=9).

Table 2.1. Categorization of Articles Based on Their Fields of Applications in Airport

Category	Topics	Applications
Security	Airport Checkpoints	Automated decision-making Checkpoints (Kyriazanos et al., 2019), Improving the accuracy of X-ray security inspection (Alshahrani, 2024; K.-W. Huang et al., 2023; Martin et al., 2015; W. Zhang et al., 2023), Baggage-tracking system (Yfantis, 1997), Randomizing checkpoints on the roadways entering the airport and canine patrol routes within the airport terminals (Pita et al., 2009), Predicting incoming passengers at the airport's security checkpoint (Viaña et al., 2023)
	Verification	Human Footsteps Biometric Verification (Costilla-Reyes et al., 2019),
	Radio Communication Networks (RCN)	Protecting RCN from external electromagnetic interference (Q. M. Chen et al., 2020)
	Unmanned Aerial Vehicles (UAV)/Drones	Distinguishing between drones and birds (Al Dawasari et al., 2023), Identifying and tracking unauthorized drones in large numbers (Esposito et al., 2023), Counter-drone systems (Çetin et al., 2022)
	Cyber Security	Detecting DDoS cyber threats for 5G aviation environment (Whitworth et al., 2023)
	Surveillance	Detecting unexplained individual activities (Albanese et al., 2014), Detecting deception from facial cues (Jupe & Keatley, 2020), Privacy-preserving video surveillance (Sugianto et al., 2021)
Administration and Management	Traffic Prediction	Airport aircraft capacity prediction (W. Du et al., 2023; Zhu et al., 2022), Multi-Airport traffic flow prediction (W. Du et al., 2024), Monthly number of flights prediction (Özmen & Pekel, 2019), low-cost passenger carrier demand prediction (Alam et al., 2024), Forecasting air travel demand (Al-Rukaibi & Al-Mutairi, 2013; Liang et al., 2022), Passenger index prediction (Xiong et al., 2022)
	Planning	DSS for total airport operations management and planning (Zografos et al., 2013), Operational aircraft maintenance planning (Papakostas et al., 2010), Predicting the required resources for each flight (Mamdouh et al., 2020), Precise prediction of arrival times at the gate (Felkel et al., 2021)

Table 2.1. (cont.)

Administration and Management	Ground Operations	DSS for efficient and safe management of apron traffic (Andreatta et al., 2014), Scheduling aircraft ground handling operations (Padrón & Guimarans, 2019), Controlling ground operations (Chatterjee & Campbell, 1999), Baggage handling system (Johnstone et al., 2010), Tracking ground equipment and vehicles (S. Wang et al., 2022), DSS for ground handling management (Ansola et al., 2012), Aircraft turnaround control system (Yıldız et al., 2022)
	Terminal Management	Terminal capacity planning decision support (Murca & Hansman, 2019), Designing optimal check-in policies (Bruno et al., 2019), Explaining the dynamics of airport terminal operations e.g. throughput of security checkpoints and passenger expenditure on discretionary activities (De Bosscher et al., 2023), Energy efficiency: Adjusting temperature set-points in the terminal building according to departure and arrival flights (Mambo et al., 2014; Sultan Qurraie & Beyhan, 2022; Sultan Qurraie & Kiraç, 2022), Gate allocation scheduling and optimization (Cai et al., 2021; Henz et al., 2004; Lim et al., 2005; Nikolić et al., 2024; S. Zhang et al., 2024), Baggage carousel allocation (J. Wang et al., 2020), Tracking the condition of multiple conveyor belts of a baggage handling system located at check-in (Bermeo-Ayerbe et al., 2023)
	Administrations/Facilities	Infrastructure expansion (Al-Juaidi, 2019), Developing airport pavement maintenance strategies by automatic detection of road stress (Abbondati et al., 2023; Kareem & Ibraheem, 2023), Accessing the sustainability of an airport (Martin et al., 2015), DSS in collaborative infrastructure planning between airport and its surrounding (Baker & Nateque Mahmood, 2012), Noise analysis and identification of airport (Sanchez-Perez et al., 2015; Tsao & Lu, 2022), Overall airport efficiency on sustainable development (Szaruga & Załoga, 2022), Modeling dynamic financial scenarios for airport infrastructure development (Gonzalez-Ruiz et al., 2019)
	Human Resource Management	Staff shift planning and Scheduling (Bruno et al., 2019; Cappanera et al., 2024; Zou et al., 2022), Airport staff burn-out identification (Jing et al., 2023)

Table 2.1. (cont.)

Airport 4.0	Automation	Types of service robots for airports (Zeng et al., 2020), Exploring the possibility of having a fully automated security system (Milbredt et al., 2022), Ideas for automatic garbage collection (Balakirsky et al., 2004)
	Internet of Things (IoT)	Smart maintenance system for baggage carts (Koenig et al., 2019), Presenting a framework for provisioning AI in IoT and 6G environments (Janbi et al., 2020), Investigate types of cyber defense tools including AI and data mining techniques for IoT in the context of the smart airport (Koroniotis et al., 2020), Cyber twins security-oriented Industrial IoT testbed (Koroniotis et al., 2023; Sultan Qurraie & Arslan, 2022)
	Smart Cites	Human-centered paradigm for cooperative hybrid cities (Streitz, 2019), Real-time crowd recognition and management system (Santana et al., 2020)
Passengers	Passenger experience	customer experience toward smart service solutions (Holz et al., 2023), Transportation and ground accessibility to airport (Pamucar et al., 2020)
	Passenger Perspective and Mindset	Qualitative research on passenger needs and perspective (Mayer, 2019), attitudes and attractiveness of AI-based transport services (Miskolczi et al., 2021), Frequent flyers behaviors (Yao et al., 2022)
	Passenger Satisfaction	The effects of big data-based services on satisfaction and repurchase intention (Ju, 2022)
Air Traffic Control (ATC)	Aircraft Sequencing	Minimizing total tardiness (Riahi et al., 2019), Sequencing and scheduling arrival flights (X.-B. Hu & Chen, 2005), Take-off scheduling (Atkin et al., 2009), Optimizing the flight turnaround (S. Zhang et al., 2024)
	Air Traffic Management	Integrating Unmanned Aerial Systems (UAS) into the airport airspace (Jenab & Pineau, 2018), Analyzing and optimizing Air Traffic Flow Management(X. Du et al., 2020; Weigang et al., 2010), Predicting flight delays (G. Chen et al., 2024)
	Flight Plans	Urgent automatic flight plan generation (Y. Yang et al., 2023), Improving route planning activities (Madanan et al., 2019), Air route network optimization (Borhani et al., 2020), Integrating all available schedule recovery options during aircraft ground operations (Evler et al., 2021)

Table 2.1. (cont.)

Air Traffic Control (ATC)	Traffic Management Strategies	Decision-making support for traffic management initiatives under uncertainty (C. Taylor et al., 2023), Integrating strategic Air Traffic Management (ATM) decision support tools with tactical ATC (Schefers et al., 2018),
	Runway, Taxi, Apron	Aircraft taxiing path planning and guidance (Deng et al., 2022; Xiang et al., 2023), Aircraft taxi time prediction (Ravizza et al., 2014), Scheduling aircraft parking (Chun et al., 2000; Jo et al., 1997), Aircraft take-off runway scheduling (Atkin et al., 2008), Optimization of airport runway resources (Deng et al., 2022), Predicting abnormal runway occupancy times based on unique radar data patterns (Friso et al., 2018), Scheduling tow and pushbacks for airplanes (Chun et al., 2000; Sandberg et al., 2014), Planning and coordination to the resilience of airport surface movement operations (Fines et al., 2020), Controlling data collection of airport flight aid light (Jia, 2014)
	Aircraft Detection	Detecting aircrafts in synthetic aperture radar (SAR) images (Lin et al., 2023), Monitoring flights taking off (Liu & Zhang, 2015)
Weather and Climate	Meteorological Services	Weather forecasting (Patriarca et al., 2023; Riordan & Hansen, 2002; Rozas Larraondo et al., 2018; F. Zhang et al., 2023), Predicting the hourly visibility of airports (Ding et al., 2022), Predicting visibility and ceiling base height (Cordeiro et al., 2021), Wind forecasting (Khattak et al., 2024; J. Kim & Lee, 2021), Predicting hot/cold waves (Zubov, 2015)
Safety	Safety Assessment System	Predicting the possible incident scenarios and determining preventative actions (Ayhan & Tokdemir, 2019), Runway crack detection/Runway condition (Maslan & Cicmanec, 2023; Midtfjord et al., 2022), Identifying latent topics and trends in aviation incidents (Kuhn, 2018), Bird detection (Krasnenko et al., 2023)

Table 2.1. (cont.)

Safety	Emergency Management	Emergency rescue management decision support system (H.-B. Du & Yu, 2009; Mijović et al., 2019), Emergency situations simulation (Bicharra et al., 2012), Emergency evacuation modeling (Ji et al., 2022)
	Pandemics and Diseases	Mask detection (Alsalamah, 2023; Alsaydia et al., 2021), Social Distancing (Sugianto et al., 2021; Teboulbi et al., 2021), Preventing the spread of disease by determining airport routes taken by infected people (Guevara et al., 2023),

2.3.3. Keyword and Abstract Analysis

The analysis of keywords, titles, and abstracts of articles by the Vosviwer program also suggested similar categorization. The results for keywords analysis with at least four times appearance demonstrate four clusters (Figure 2.5). Again, it can be observed that topics such as airport security, air traffic management and control, weather forecasting, and airport safety appeared in the analysis, as previously mentioned.

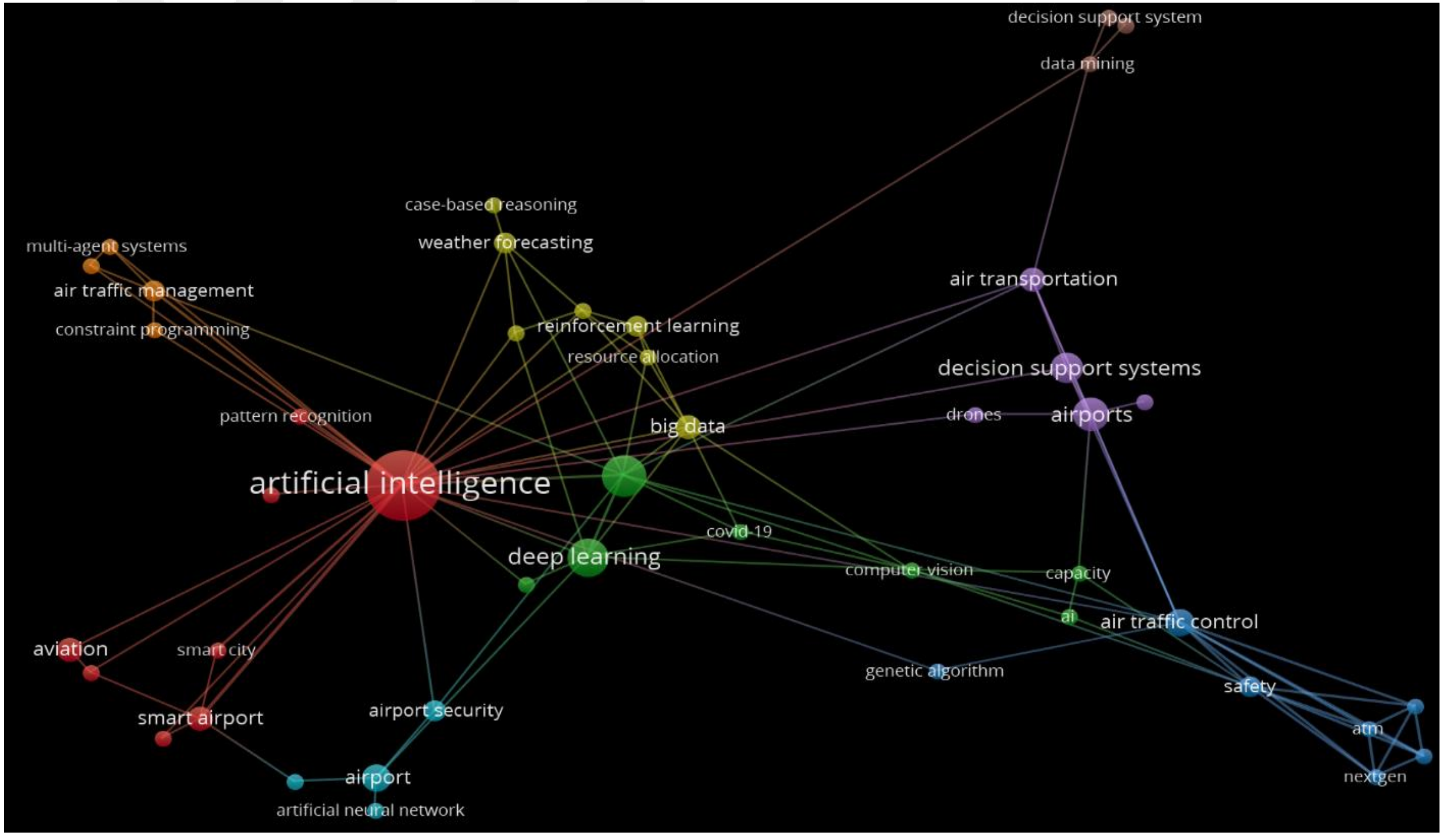

Figure 2.5. Analysis of Keywords with at Least Four Appearances

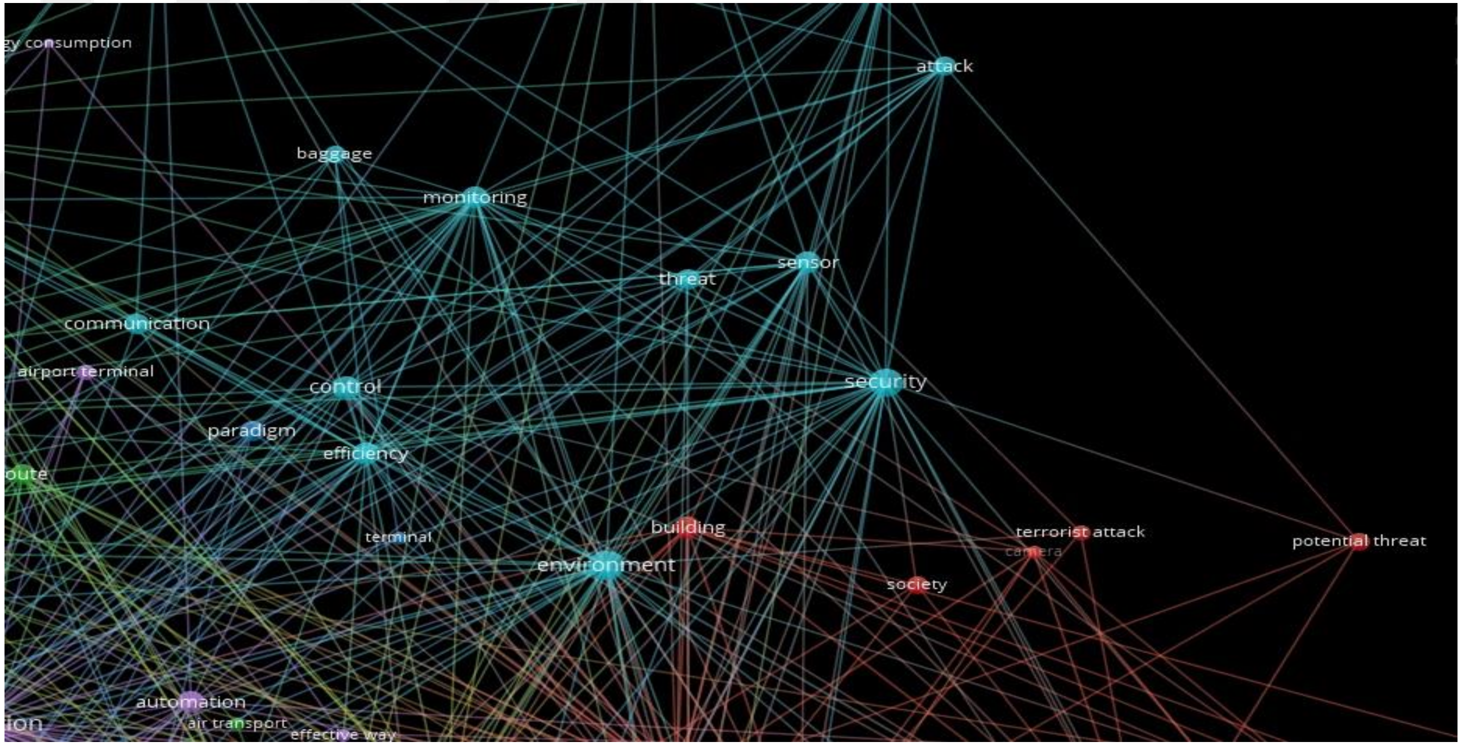

Figure 2.6. Cluster 1: Security

Similarly, the title and abstract analysis of articles show five distinguished clusters of topics that are similar and related to the stated categories in Table 2.1. Cluster number 1, illustrated in Figure 2.6 shows the topics related to airport security. Security was also one of the most studied topics with many subcategories, as stated in Table 2.1.

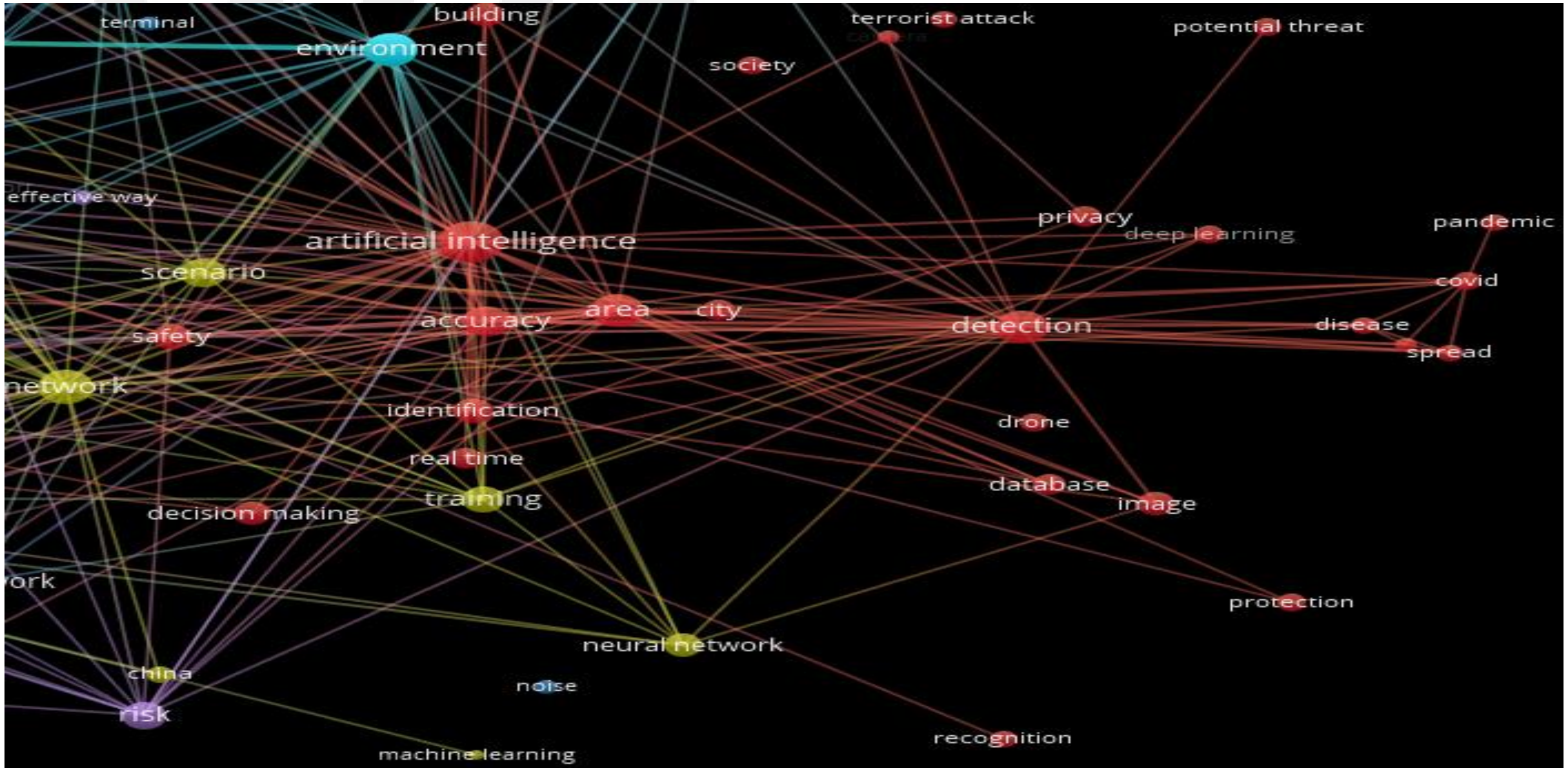

Figure 2.7. Cluster 2: Safety

Cluster 2 (Figure 2.7.) illustrates topics related to the safety category. It shows the intensity of relationships between topics such as flight scheduling, decision support for runway and airspace management, and flight delays. Clusters 2 and 3 are closely related to each other and share common titles such as privacy, camera, potential threat, and terrorist attack. This result was expected since safety and security can be considered as parallel topics.

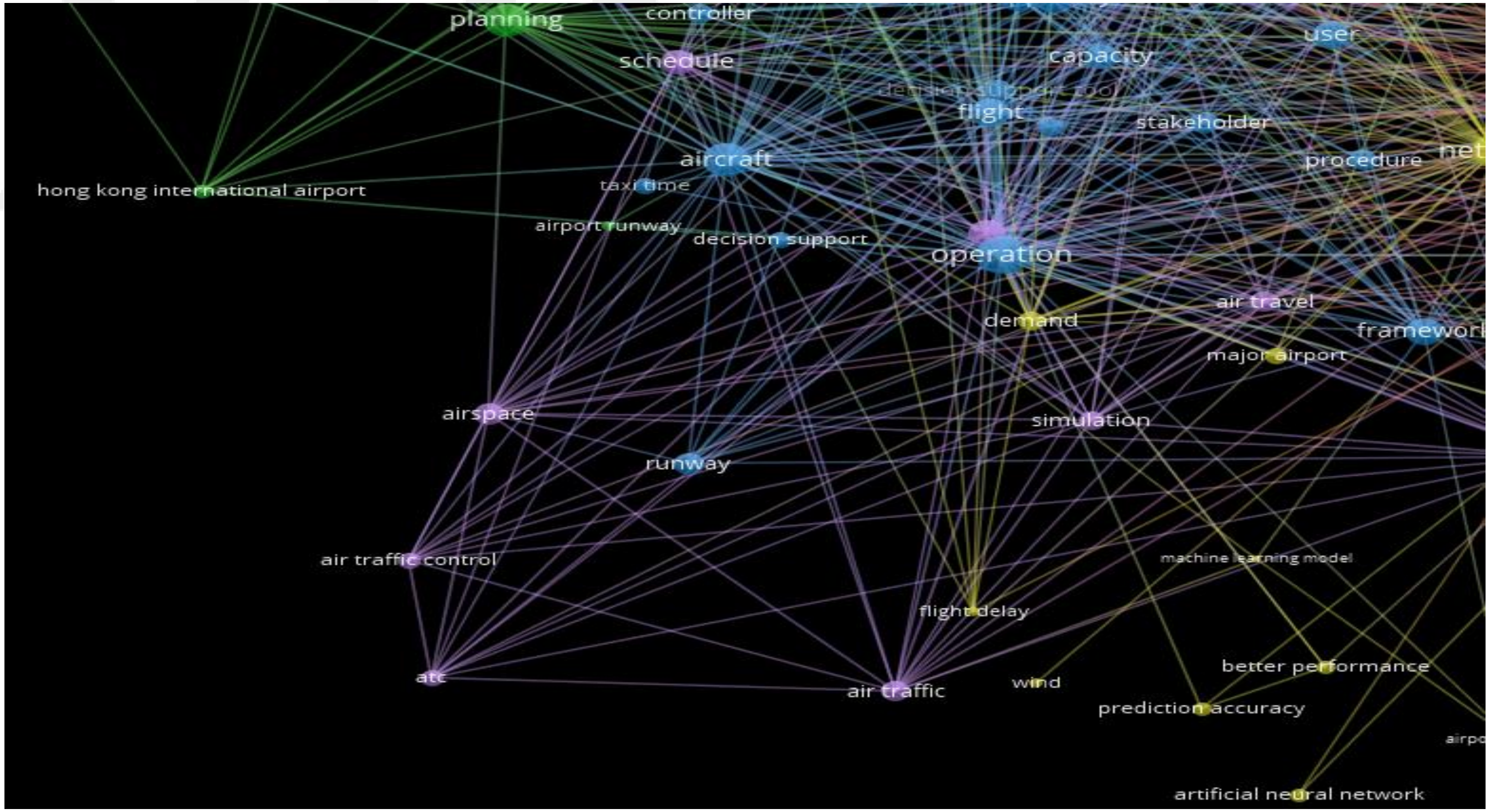

Figure 2.8. Cluster 3: Air Traffic Control (ATC)

Cluster 3, shown in Figure 2.8 illustrates topics related to the Air Traffic Control (ATC) category. It shows the intensity of relationships between topics such as flight scheduling, decision support for runway and airspace management, and flight delays.

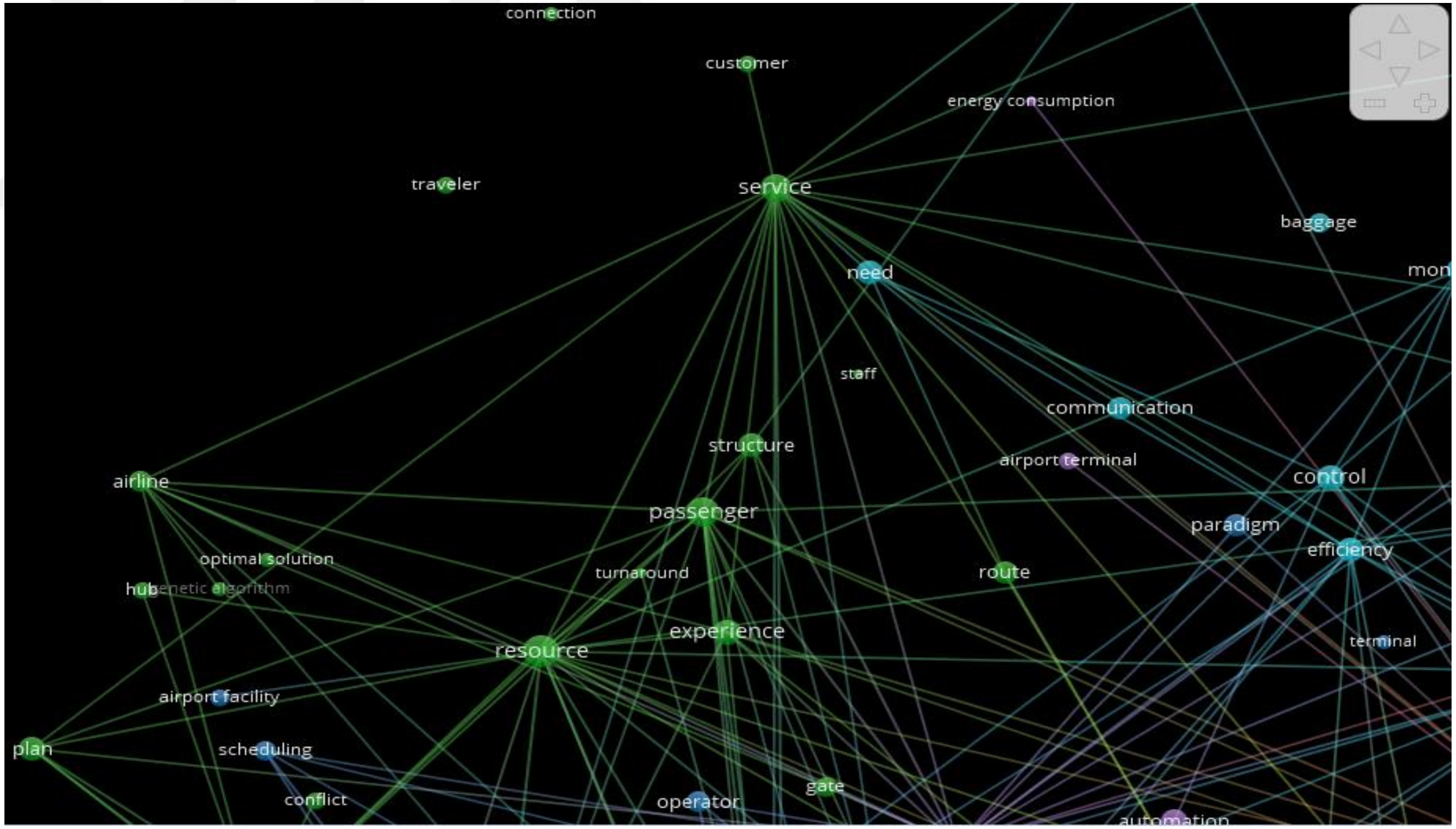

Figure 2.9. Cluster 4: Passengers and the Management of Airports

Figure 2.9 shows cluster 4, which includes topics related to passengers, terminal operations, and services in airports. This cluster can be considered a combination of passengers and the administration and management categories in Table 2.1.

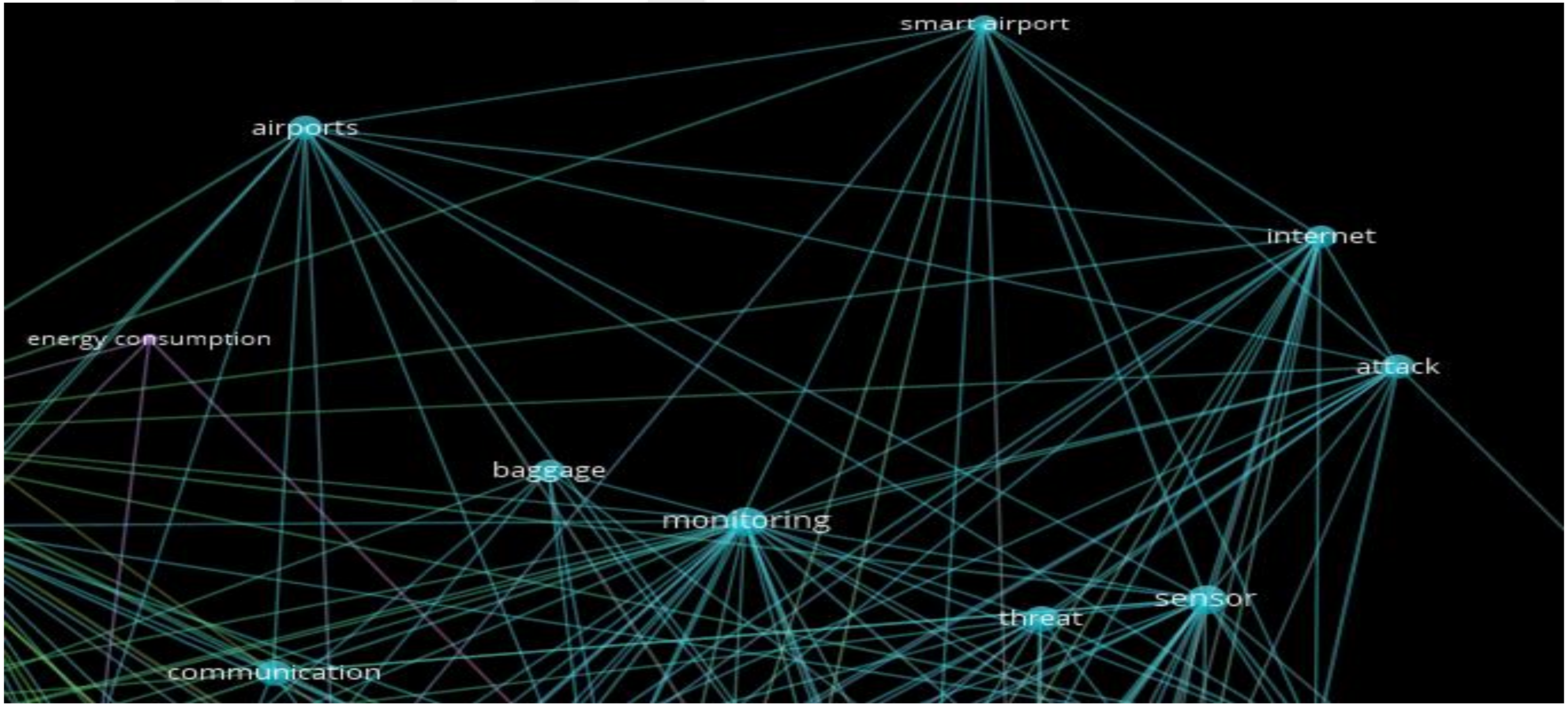

Figure 2.10. Cluster 9 Representing Airport 4.0

Cluster 4, shown in Figure 2.10,represents the Airport 4.0 category in Table 2.1. It includes topics related to smart airports, 5G infrastructure, and sensors while sharing common topics with cluster 1 (security category).

2.4. Discussion

2.4.1. Security

The articles for this category cover topics such as airport checkpoints, drone detection, radio communication networks, cyber security, and surveillance. The most studied topic for this category was airport checkpoints, with eight articles. AI-powered baggage scanners, equipped with deep learning algorithms, can meticulously analyze X-ray scans in airport checkpoints with superior accuracy and efficiency compared to traditional methods (Alshahrani, 2024; K.-W. Huang et al., 2023). This not only significantly reduces false alarms, minimizes passenger inconvenience, and expedites security checks but also allows security personnel to focus their expertise on anomalies flagged by the system.

Surveillance is another popular topic among AI researchers. AI-driven video surveillance goes beyond passive monitoring. Autonomous detection of suspicious objects or activities (e.g., irregular movements or attempts to avoid security checks) can, with the help of AI-driven video surveillance, significantly enhance the security of airport terminals (Albanese et al., 2014). Additionally, analyzing real-time footage can identify individuals on watch lists with facial recognition, enabling a rapid response (Jupe & Keatley, 2020). This empowers security personnel to intervene and investigate potential threats proactively.

Finally, airports are faced with new security challenges as unmanned aerial vehicles (UAVs), known as drones, have gained popularity for entertainment and commercial purposes. Unauthorized drones can disrupt airport operations, causing delays and cancellations. Collisions of drones with aircraft, especially during take-off and landing, can be catastrophic. Moreover, drones could be used for terrorist attacks by carrying weapons or explosives. AI-powered systems can detect drones in large numbers with high accuracy (Al Dawasari et al., 2023). Early detection and tracking of drones allow authorities to identify potential threats and take necessary steps to countermeasure actions (Çetin et al., 2022).

2.4.2. Administration and Management

The most studied category was related to the management of various departments and facilities in airports. It includes topics such as traffic prediction of passengers in airports, terminal management and planning, ground operation management, human resource management, and administration of facilities. The emergence of AI technology in several operational fields for planning and decision-making is providing game-changing solutions (W. Du et al., 2023; Zhu et al., 2022). With the help of AI algorithms, airports can forecast passenger numbers accurately by analyzing variables such as flight schedules, weather, holidays, and other events (Al-Rukaibi & Al-Mutairi, 2013; Liang et al., 2022; Özmen & Pekel, 2019).

Furthermore, AI-based passenger traffic prediction enables airports to allocate resources proactively, anticipating peak periods so that passengers have a smooth travel experience. In fact, gate allocation and scheduling based on the terminal traffic and available resources was one of the most studied topics according to obtained results (Cai et al., 2021; Henz et al., 2004; Lim et al., 2005; Nikolić et al., 2024; S. Zhang et al., 2024). Such predictive capability enables airports to optimize staffing levels, streamline security procedures, and improve overall efficiency prediction (W. Du et al., 2024; Murca & Hansman, 2019). AI also provides these options for airport operators to optimize shift scheduling using AI-based workforce management systems, by accounting for factors such as employee preferences, labor regulations, and peak traffic times, thereby minimizing labor costs while maintaining appropriate staffing levels to avoid employee burnout (Bruno et al., 2019; Cappanera et al., 2024; Zou et al., 2022). Additionally, AI-driven insights empower airport authorities to make informed decisions regarding infrastructure development and capacity planning, ultimately enhancing the overall operational resilience of airports (Al-Juaidi, 2019; Baker & Nateque Mahmood, 2012).

Artificial intelligence is also revolutionizing ground operations at airports by optimizing various aspects such as aircraft movements (Andreatta et al., 2014; Padrón & Guimarans, 2019), baggage handling (Ansola et al., 2012; Chatterjee & Campbell, 1999; Johnstone et al., 2010), and ground vehicle management (Ansola et al., 2012; S. Wang et al., 2022). Additionally, AI-driven predictive maintenance systems monitor the condition of pavement ground vehicles and equipment, forecasting maintenance needs before their failure and causing disruptions (Abbondati et al., 2023; Bermeo-Ayerbe et al., 2023; Kareem & Ibraheem, 2023; Koenig et al., 2019).

2.4.3. Airport 4.0

One of the understudied categories was airport 4.0, also known as smart airports. This category involved only nine articles, four of which were qualitative. Topics such as robots and automation, the Internet of Things (IoT), and smart cities were included in this category. Through automation, airports can streamline various processes (Zeng et al., 2020), from check-in and security screening (Milbredt et al., 2022) to cleaning (Balakirsky et al., 2004) and maintenance (Koenig et al., 2019). IoT devices embedded throughout the airport infrastructure, such as sensors and cameras, collect real-time data on passenger flow, terminal conditions, and equipment status (Janbi et al., 2020)(Qurraie, 2022). AI algorithms then analyze this data to optimize operations, predict potential issues, and improve resource allocation. By integrating with city-wide IoT networks, airports can facilitate seamless multimodal transportation, enabling passengers to transition between air travel and other modes of transportation seamlessly (Santana et al., 2020).

2.4.4. Passengers

The least studied category, with only six articles, was related to passengers and their point of view toward AI. It is worth noting that two of these six articles encompass qualitative studies. In this category, three parallel topics related to AI were discussed: passenger experience, passenger mindset, and satisfaction. The first topic, passenger experience, delves into how passengers interact with AI systems during their air travel journey (Holz et al., 2023). It explores aspects such as ease of use, convenience, and overall satisfaction with AI-powered services or solutions integrated into the travel experience (Pamucar et al., 2020).

Studies on the passenger's mindset focus on understanding passengers' attitudes, beliefs, and perceptions regarding AI technology in the context of air travel (Miskolczi et al., 2021). It aims to uncover passengers' thoughts on the integration of AI, their trust in AI systems, and any concerns or reservations they may have (Yao et al., 2022). Finally, the study regarding passenger satisfaction examines the extent to which passengers feel fulfilled, content, or pleased with their AI-enhanced travel experiences. It considers factors such as meeting expectations, delivering value, and providing a seamless journey, ultimately aiming to gauge overall satisfaction levels among passengers using AI in air travel (Ju, 2022).

2.4.5. Air Traffic Control

Another category that has been studied in great numbers is related to operations and tasks of the Air Traffic Control department in airports. Integrating artificial intelligence (AI) into air traffic control systems promises a transformative shift in aviation operations. By leveraging AI algorithms, air traffic controllers can access real-time insights and decision support tools, enhancing their ability to manage complex traffic scenarios efficiently and safely. The topics for this category include air traffic management, aircraft sequencing, flight plans, establishing strategies for traffic management, runway and taxiway management, and aircraft detection.

One of the critical tasks of airport control towers is to safely and efficiently manage air traffic (X. Du et al., 2020; Weigang et al., 2010). AI showed great potential for assisting the control tower with scheduling (Atkin et al., 2009), sequencing (X.-B. Hu & Chen, 2005), predicting (G. Chen et al., 2024), and optimizing (Riahi et al., 2019; S. Zhang et al., 2024) upcoming and ongoing aircraft traffic. In addition, there are also air route planning and optimization (Borhani et al., 2020; Madanan et al., 2019) and integration of other aerial systems and airspaces with airport ATC (Evler et al., 2021; Jenab & Pineau, 2018; Schefers et al., 2018).

Management of the runways, taxiways, and apron of an airport is another critical task that takes up a significant amount of time for air traffic controllers in an airport. Artificial intelligence systems can analyze vast amounts of data from radar, weather forecasts, and flight schedules to optimize paths (Deng et al., 2022; Friso et al., 2018; Xiang et al., 2023), parking, sequencing (Atkin et al., 2008), allocating resources (Chun et al., 2000; Sandberg et al., 2014) and spacing and parking of aircraft (Chun et al., 2000; Jo et al., 1997), ultimately reducing delays and increasing airspace capacity for all three areas (Deng et al., 2022; Xiang et al., 2023). Moreover, AI-driven predictive analytics can anticipate potential safety hazards and operational disruptions in these three dynamic areas of an airport, enabling proactive risk mitigation measures (Friso et al., 2018).

2.4.6. Weather and Climate

The category for weather and climate has the least diversity of topics in the studies. The articles for this category only discussed the use of AI for meteorological services that are related to airport operations. AI can help airports by offering unprecedented accuracy and efficiency in weather forecasting and analysis (Khattak et al., 2024; J. Kim & Lee, 2021). Through advanced machine learning algorithms such as weather anomaly detection and hierarchical clustering, AI systems can process vast amounts of meteorological data from various sources (Patriarca et al., 2023; Rozas Larraondo et al., 2018; F. Zhang et al., 2023). This enables airports to anticipate weather patterns with greater precision, improving safety and operational efficiency for airports. Moreover, AI-powered predictive models can forecast weather conditions days or even hours (Ding et al., 2022) in advance, allowing airports to make informed decisions regarding flight schedules, runway operations, and ground services (Cordeiro et al., 2021; Zubov, 2015). Additionally, AI algorithms can detect and predict severe weather events, enabling airports to implement proactive measures to mitigate potential disruptions and ensure passenger safety (Zubov, 2015).

2.4.7. Safety

For the safety category, three main topics were discussed. The first topic was related to Safety Assessment Systems (SAS). SAS refers to comprehensive frameworks and processes designed to evaluate, manage, and mitigate risks within various contexts (Maslan & Cicmanec, 2023). These systems encompass various procedures and technologies aimed at identifying potential hazards and risks within airport operations. AI can enhance SAS by utilizing advanced algorithms to analyze broad amounts of data collected from security cameras, sensors, and other surveillance systems (Kuhn, 2018). Moreover, AI algorithms can analyze past data to identify patterns, enabling airports to proactively address potential safety hazards before they escalate (Ayhan &

Tokdemir, 2019). For instance, the AI-based SAS systems showed a significant improvement in the automatic detection and evaluation of the runway surface for cracks and other hazards with the help of drone imagery (Maslan & Cicmanec, 2023; Midtfjord et al., 2022).

Another prominent application of AI for improving airport safety is for Emergency Management Systems (EMS). By leveraging predictive analytics, AI algorithms can predict potential emergency scenarios and even create similar simulations (Ji et al., 2022), which enables airports to allocate resources efficiently for such scenarios and prepare precautionary actions and response strategies (H.-B. Du & Yu, 2009; Mijović et al., 2019). Additionally, AI-driven analytics provide post-incident assessment, enabling airports to optimize their responses by learning past mistakes and strengthening resilience against future emergencies (Bicharra et al., 2012).

Following the COVID-19 pandemic, unpredictable flight schedules and new health screening protocols emphasizing social distancing have disrupted many operational planning and orders for airports. Consequently, the use of AI to fight against the pandemic has increased. AI-driven predictive models can analyze big data, including travel patterns, passenger health records, and epidemiological data, to forecast the spread of diseases and identify high-risk areas or individuals (Guevara et al., 2023). In addition, AI-powered surveillance systems can detect symptoms or violations of precautionary measures such as wearing masks (Alsalamah, 2023; Alsaydia et al., 2021) or social distancing (Sugianto et al., 2021; Teboulbi et al., 2021) in real-time.

2.5. Conclusion

Artificial intelligence presents a wide variety of solutions with tons of opportunities for airports, promising a future of smoother operations, enhanced security, and a more positive passenger experience. By streamlining processes, optimizing resource allocation, and leveraging data for predictive capabilities, AI can significantly improve airport efficiency. As AI technologies continue to evolve, their integration within airports has the potential to revolutionize air travel.

This study presented a scoping review of previous articles regarding the application of artificial intelligence in airports. The result of this study states that the categories most studied belong to administration and management, air traffic control, and security. This result indicates that most research focused on the fields that have the potential to optimize airport operations, enhance safety, and improve the overall performance of airports. Theoretical topics such as passenger perspective toward the use of artificial interleague or airport 4.0 were given less attention by scholars. Interestingly, these two categories were the only ones that involved qualitative studies. The perspective of passengers has remained in the shadows. Neglecting passengers and their preferences risks rendering many AI applications for airports irrelevant and ineffective.

Although AI provides innovative and promising solutions to many growing issues for the industry, their adoption, especially regarding passenger experience, has been slow so far. Despite all the remarkable innovations in data science, from self-technology check-in to cleaning robots to chatbots, it seems we have a long way to go before passengers can see practical and feasible interactions with AI during their air travels.

Consequently, there is a pressing need for further research to investigate into the passengers' viewpoint regarding AI-based solutions, ensuring that such technologies are tailored to their needs. Integrating AI with existing airport technologies that directly interact with passengers is a promising topic that needs further investigation. One notable technology in this context is interactive kiosks. Kiosks offer a multitude of functionalities, ranging from check-in and baggage drop-off to boarding pass issuance and flight information retrieval (Bogicevic et al., 2017; Vakulenko et al., 2018). By automating these tasks, airports were able to significantly reduce wait times, alleviate congestion at traditional check-in counters, and improve overall operational efficiency (Antwi et al., 2021; Drennen, 2011; Kim et al., 2019).

The integration of artificial intelligence AI can provide game-changing competitive advantages for airports. AI-powered kiosks can analyze passenger data, predict wait times, and optimize resource allocation accordingly. Furthermore, advanced AI algorithms enable kiosks to provide personalized recommendations, such as suggesting preferred seating options or suggesting nearby amenities based on passenger preferences. Beyond operational efficiency, AI-driven kiosks contribute to enhanced passenger experience. Natural language processing capabilities allow for intuitive interactions, enabling passengers to ask questions and receive clear, concise information. Additionally, biometric authentication systems powered by AI offer secure and convenient access to kiosk services.

By understanding factors that shape passengers' attitudes and behaviors toward such technologies, airport authorities can design kiosks based on the passenger's needs, which will eventually increase the number of users. As a result, researchers should be encouraged to follow this line of research and investigate the behavioral intention and use behavior of passengers from different perspectives.

CHAPTER III

THEORETICAL BACKGROUND AND HYPOTHESIS DEVELOPMENT

This chapter examines the theoretical and conceptual frameworks of the dissertation. In addition, it discusses the proposed hypothesis. It delves into the literature by focusing on the theoretical background and existing models for technology acceptance and service quality measurements.

3.1. Self Service Technology

The emergence of information and communication technology stands as one of the most significant advancements shaping societies over the last century. This rapidly growing field is assured to bring fundamental changes across societies (Haji Amiri et al., 2022). Today, integrating and utilizing information technology systems are topics of discussion in every organization in both the public and private sectors (Mammadli & Klivak, 2020). A critical aspect of this evolution is the development of self-service technologies (SSTs).

With the evolution of self-serve technologies, the concept of self-service has moved from traditional techniques like diners helping themselves at buffets to more advanced technology such as Human-Computer Interaction (HCI). These technologies empower customers to complete tasks traditionally requiring independent interaction with a service employee. From automated teller machines (ATMs) to online travel booking platforms, SSTs permeate various industries, offering convenience and efficiency (Curran & Meuter, 2005b; Haji Amiri, 2019).

This transformation has been driven by technological advancements that have streamlined and simplified the self-service experience. While the concept of self-service in customer interactions has existed for decades, the term "Technology-Based

Self-Service" (TBSS) was first introduced by Dabholkar (1996) in their 1996 publication. This specific term emphasizes the role of technology in empowering customers to independently complete tasks, differentiating it from traditional self-service options that may not involve technology (e.g., filling out a paper form). Since then, scholars such as Ladik (2003) and Anselmsson (2001) have further explored and expanded upon the concept of TBSS, contributing to a deeper understanding of its impact on various aspects of service delivery.

To its core concept, SST represents a novel approach to service delivery that eliminates the need for direct interaction between customers and service providers (Meuter et al., 2000a). Instead, customers gain greater control over service delivery, performing tasks or portions of tasks independently through technology-enabled interfaces (Anselmsson, 2001; Globerson & Maggard, 1991). This shift has been facilitated by advances in technology, enabling SSTs to provide seamless and efficient self-service experiences.

3.2. Organizations and Technology Acceptance

In contemporary organizations, the prevalence of computers and information technology has significantly expanded. Estimations suggest that since the 1980s, nearly 50% of organizational investments have been allocated to information technology (Westland & Clark, 2001). However, for technology to advance, it must be accepted and adopted by customers or employees within organizations. The exploration of user acceptance of new technologies stands as one of the most researched topics in the information systems literature (P. J. Hu et al., 1999). The research in this field has concluded several different theoretical models with the origin of information systems, psychology and sociology, which usually explains 40% of the variance in the individual purpose use of technology (S. Taylor & Todd, 1995b).

Over the past two decades, a substantial portion of management information systems studies has concentrated on identifying factors that influence technology adoption and usage behavior. This focus has resulted in the development of several theoretical models in the field, with the most prominent and widely utilized ones discussed below.

3.3. Theoretical Background of Technology Acceptance

Information systems (IS) research has extensively investigated the factors influencing the acceptance of new technology among individuals. Within this broad field, various research streams have emerged. One focuses on individual technology acceptance, with the purpose or application as the dependent variable (Davis, 1989; Davis et al., 1989a). Others explore organizational implementation success, technology fit with job roles and related areas. Each of these disciplines offers unique insights into user acceptance of information technology, emphasizing theoretical models that treat usage as a dependent variable (Venkatesh et al., 2003). The role of purpose in predicting behavior is pivotal and well-established in IS literature and theories.

Figure 3.1 presents the foundational conceptual framework underlying a group of models that explain individual technology acceptance, forming the basis of this study. This research identifies and analyzes eight key theoretical models.

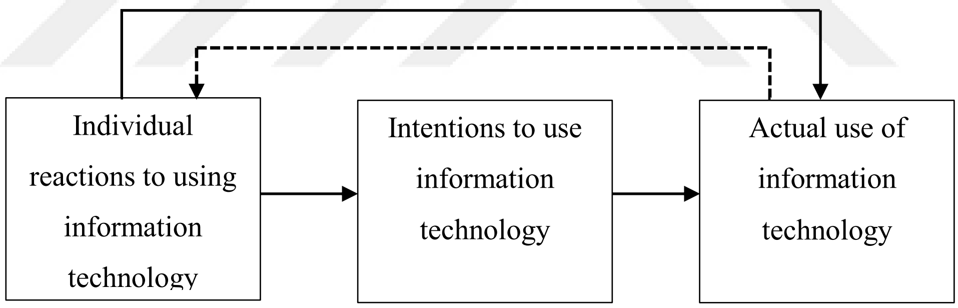

Figure 3.1. Fundamental Concept Underlying Models of User Acceptance

Source: Venkatesh et al., 2003

3.4. Existing Models and Theories for Technology Acceptance

A variety of models have been employed to elucidate the deployment of information technology. These models are derived from either theoretical basis or empirical observations and experiences. Theoretically informed models often draw on change or behavioral theories, positing that attitudes, behavioral intentions, or direct behavioral changes influence technology acceptance and implementation. Such models provide a structured framework for understanding the factors driving technology adoption.

Numerous models exist to identify the determinants of technology utilization within organizations, including:

3.4.1. Diffusion of Innovation Theory

Perhaps one of the oldest theories for describing individual behavior toward a new technology was developed by Roger in 1962. The diffusion of innovations theory explores how new ideas and technologies spread within a population. Introduced by Everett Rogers in his book “Diffusion of Innovation”, the theory investigates the factors influencing the rate of adoption and the reasons behind it (Rogers, 1995). This framework has been widely applied to understand the adoption of innovations within organizational management (Orr, 2003).

Diffusion of Innovation theory investigates the social mechanisms underlying the adoption and dissemination of innovations within a social system (Momani et al., 2017). In this theory, new ideas, new practical methods, and the use of new means and tools or new goals are the main points of discussion. Roger’s theory explains how ideas or products gain momentum over time and spread through a specific population or social system. The end result of this diffusion is that people, as part of a social system, adopt a new idea, behavior, or product. Adoption is defined as a shift in behavior involving the acquisition or utilization of a new product or the initiation of a new practice (Rogers, 1995, p250-251). This process necessitates the perception of the innovation as new or distinct.

According to Rogers (1995), there are five significant factors that affect individuals’ intentions to adopt innovation (Figure 3.2). From his point of view, these characteristics affect the confidence coefficient of a person's acceptance of innovation. These features include:

- Relative advantage: The degree to which an innovation is perceived as superior to existing alternatives.
- Complexity: The degree to which an innovation is perceived as easy to understand and use.
- Trialability: The degree to which an innovation can be experimented with or piloted.

- Observability: To the extent that the results and consequences of an innovation are tangible and visible to others.
- Compatibility: The degree to which an innovation aligns with potential users' values, prior experiences, and needs.

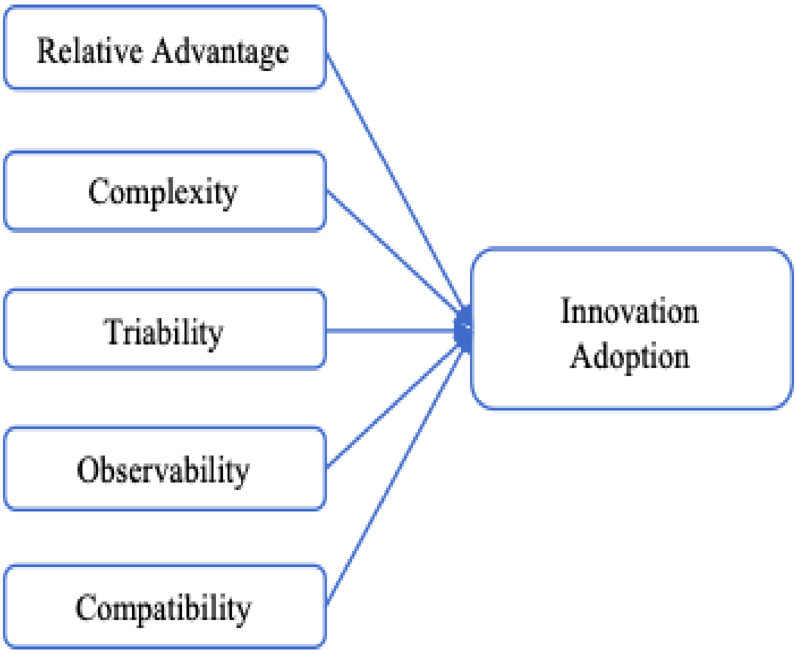

Figure 3.2. Factors That Affect Individuals' Intentions to Adopt Innovation

Source: Roger, 1995

According to Rogers (1995), innovations that are less complex but have higher scores in other characteristics. He also classified people into different degrees based on how receptive they are to innovation: innovators, early adopters, early majority, late majority, and laggards. The figure below (Figure 3.3.) illustrates that as successive groups of consumers adopt the new technology (depicted in blue), its market share (in yellow) will eventually reach saturation.

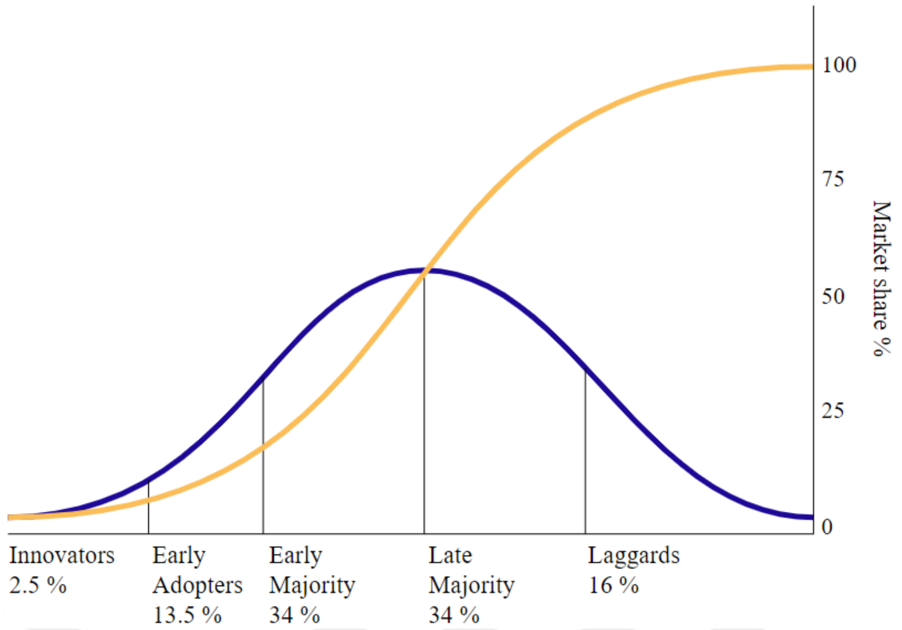

Figure 3.3. Classification of Individuals based on Their Innovation Acceptance

Source: Rogers, 1995

3.4.2. Theory of Reasoned Action

The theory of reasoned action, introduced by Fishbein and Ajzen (1977), originates from the field of social psychology and stands as one of the foremost and efficacious theories employed to explain human behavior. In their book, "*Belief, attitude, intention and behavior: An introduction to theory and research*", they have proposed that the link between individual and social beliefs related to a specific behavior determines a person's willingness to perform or not perform the desired behavior (Fishbein & Ajzen, 1977).

In fact, the theory of reasoned action attempts to determine the relationship between the beliefs, attitudes, norms, desires, and behaviors of a person by considering the following two assumptions: 1) Humans are rational beings with the ability to process and use information 2) Humans use information processing to reach a logical decision (Davis et al., 1989b).

In this model, behavioral intention and personal norms play pivotal roles in shaping behavior. Accordingly, the use of technology is influenced solely by the intention to use it (Momani et al., 2017). The theory of reasoned action states that behavior is exclusively driven by behavioral intention, reflecting individual will and determination. In short, a person's behavior is determined by their desire to do it, which in turn is determined by their attitudes and mental norms towards behavior (Figure 3.4.)

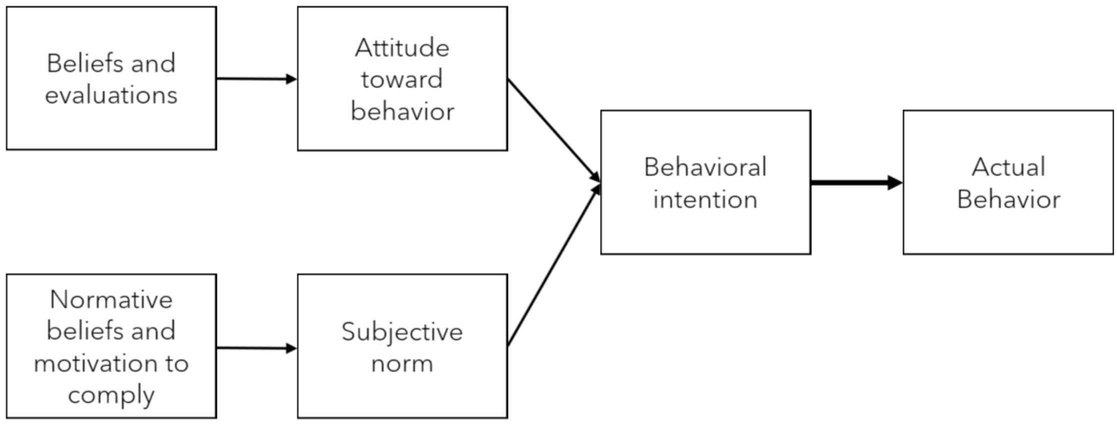

Figure 3.4. Theory of Reasoned Action

Source: Fishbein and Ajzen, 1977

The main elements of this theory are as follows:

- **Behavioral Beliefs**: A set of personal beliefs about the types of behaviors that are desirable in general and help a person to decide whether a particular behavior is desirable or not. Behavioral beliefs strongly influence a person's attitude about the desirability of any particular behavior. These beliefs are the precondition and background of attitude towards certain behaviors.
- **Attitudes**: beliefs that a person forms during his life, which can be formed by direct experiences or external information or by the individual. However, not all beliefs influence attitudes towards behavior; only certain ones—referred to as salient beliefs—directly impact attitudes (Ajzen, 1980). Therefore, attitude towards behavior represents an individual's personalized beliefs about the likely outcomes of their actions, whether positive or negative. Essentially, it reflects their emotional inclination toward performing the behavior.
- **Normative Beliefs**: A set of beliefs that are formed based on the perspectives of significant social groups (reference groups) in an individual's life, such as friends, colleagues, and superiors, regarding the appropriateness of engaging

in a behavior. These beliefs wield considerable influence over personal norms as well.

- **Subjective Normas**: It refers to the social pressures associated with either performing or avoiding toward a specific behavior. In essence, this normative component relates to how the social environment can influence an individual's behavior, as well as their perception and belief about whether important people or groups (reference groups) endorse or disapprove of the behavior.
- **Intention**: It is the conscious process of deciding to engage in behavior.
- **Behavior**: It refers to the implementation and continuation of desired behavior.

It is worth noting that Ajzen (1980) pointed out that there are other variables outside the model that may influence individual tendencies, but it is assumed that these variables can influence tendencies only in the context that they can influence individual attitudes or norms. Still, all these elements are pivotal in shaping an individual's readiness and decision-making process regarding behavior.

3.4.3. Theory of Planned Behaviour

The theory of planned behavior has been proposed by Ajzen (1985) as a developed model of the theory of reasoned action for situations where people do not have complete control over their behavior. Adding the construct of perception of behavioral control increases the predictive power of the theory, especially in situations where the individual believes that he does not have complete control over his ability to perform the behavior. In short, this theory tries to predict involuntary behaviors by introducing the construct of perceived behavioral control (Momani et al., 2017).

Ajzen (1985) has developed and expanded the theory of rational action by adding the construct of perception of behavioral control to consider individual perceptions of the availability of knowledge, resources, facilitating conditions, and opportunities to perform behavior. Therefore, in this theory, behavioral intention is determined by three factors: attitude, subjective norms, and perception of behavioral control (Figure 3.5), each of which is created by a number of related beliefs and evaluations.

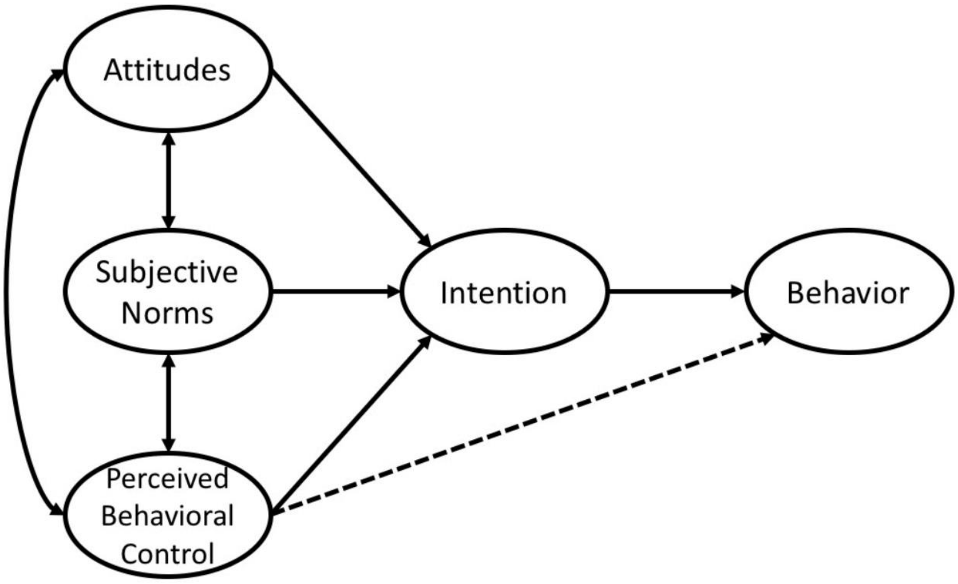

Figure 3.5. Conceptual Framework of the Theory of Planned Behavior

In the theory of planned behavior, the behavior itself is a function of behavioral intention and perception of behavioral control. According to Ajzen (1991), human behavior is influenced by the belief regarding the consequences of a behavior (behavioral beliefs) and the evaluation of these consequences. Next, there is a belief concerning the expectations of others and the motivation to comply with these expectations (normative beliefs). Finally, there is the belief about the existence of factors that may facilitate or hinder performance. Figure 3.6. explains this theory in more detail.

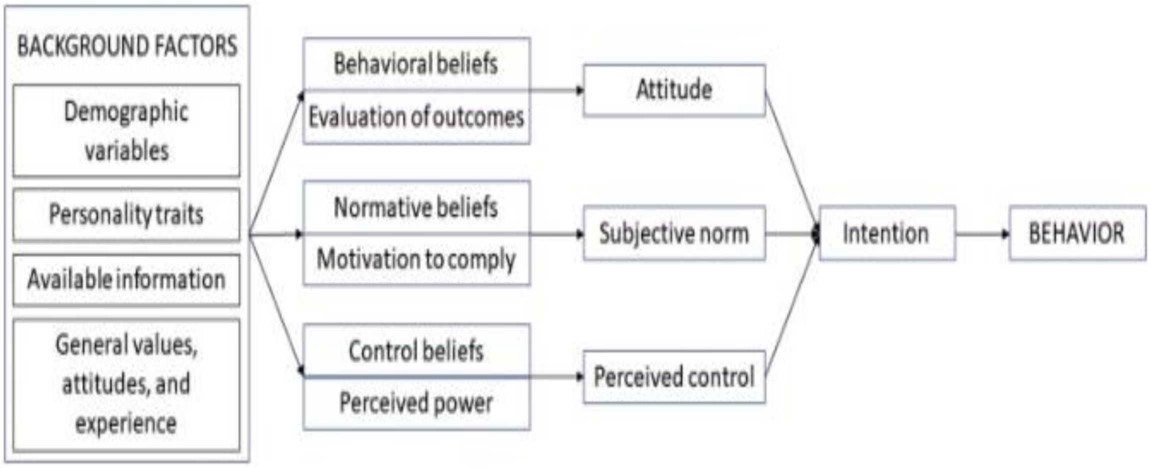

Figure 3.6. The Theory of Planned Behavior with all Underlying Factors

Source: Ajzen, 1985

Normative beliefs contribute to the formation of subjective norms, while perceived behavior control beliefs influence the formation of behavioral intentions. Generally, a more favorable attitude, stronger norms, and greater perceived behavioral control strengthen the intention to perform a behavior practically. Subsequently, this intention progresses to the action stage, culminating in the actual performance of the behavior (Ajzen, 1980).

Later, Taylor and Todd (1995a) proposed the Decomposed Theory of Planned Behavior, in which constructs from Ajzen's theory of planned behavior are combined with Rogers' theory of diffusion and innovation (S. Taylor & Todd, 1995a). By analyzing the constructs of attitude, norm, and perceived behavioral control, they expanded the theory of planned behavior. This work led to an increase in the explanatory power of behavioral intention and a more accurate understanding of the antecedents of behavior (Momani & Jamous, 2017).

3.4.4. Technology Acceptance Theory (TAM)

The Technology Acceptance Model (TAM), introduced by Fred Davis in 1989, aims to predict and explain how organizations adopt and utilize technologies, making it one of the most extensively researched models in technology acceptance (Momani et al., 2017). The model is a modification of the theory of reasoned action that Davis proposed in his doctoral dissertation. The main purpose of the technology acceptance model is to provide a basis for tracking the effect of external factors on internal beliefs, attitudes, and intentions to use (Davis, 1989). Validated across various research domains and technological applications, TAM explains the factors influencing user acceptance or rejection of specific technologies.

Built upon the theory of reasoned action, TAM claims that two key factors, perceived ease of use and perceived usefulness of computer systems, shape an individual's attitude towards technology (Figure 3.7.).

This attitude, in turn, influences behavioral intentions, ultimately translating into actual system usage. According to TAM, the use of information technology is driven by the intention to use a particular system, which itself is influenced by the perceived usefulness and ease of use of the system from the user's perspective.

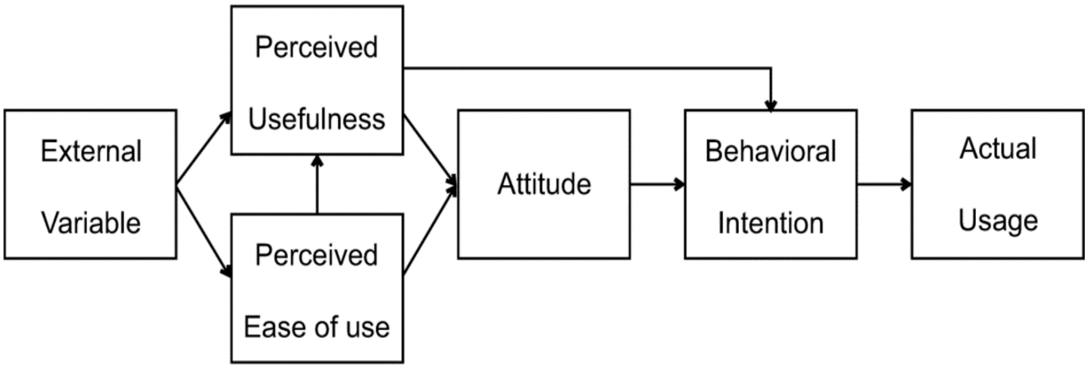

Figure 3.7. The Original Model for the Technology of Acceptance Theory

Source: Davis, 1989

The main elements of TAM are as follows:

- **Perceived usefulness** is defined as the extent to which an individual believes utilizing a specific system will enhance performance. Previous research consistently indicates that systems perceived as more useful are more likely to be adopted and used by individuals (Momani et al., 2017).
- **Perceived ease of use** is defined as the extent to which a person believes that using a particular system in terms of physical or mental effort and learning does not require much effort. Systems that are more difficult to learn and use are less likely to be widely used.
- **Attitude** is defined as a person's positive or negative feelings about performing a behavior.
- **Behavioral intention** is defined by the individual's probability of using the system.
- **Actual usage is** defined as the use of the system in a complete and continuous manner.

The TAM model assumes that the usefulness and ease of use will improve people's reaction to the innovation, and their willingness to accept it will increase. In this model, usefulness plays a pivotal role by directly influencing behavioral intention and significantly contributing to the formation of attitude. It also acts as a mediator, facilitating the impact of ease of use on behavioral intention. Ease of use is a secondary factor that has a direct effect only on attitude towards use (Hong et al., 2002).

Given the inconsistent and complex nature of the relationship between attitude and behavioral intention within the Technology Acceptance Model (TAM), Venkatesh and Davis (1996) have proposed a revised model excluding the attitude construct (Figure 3.8.)

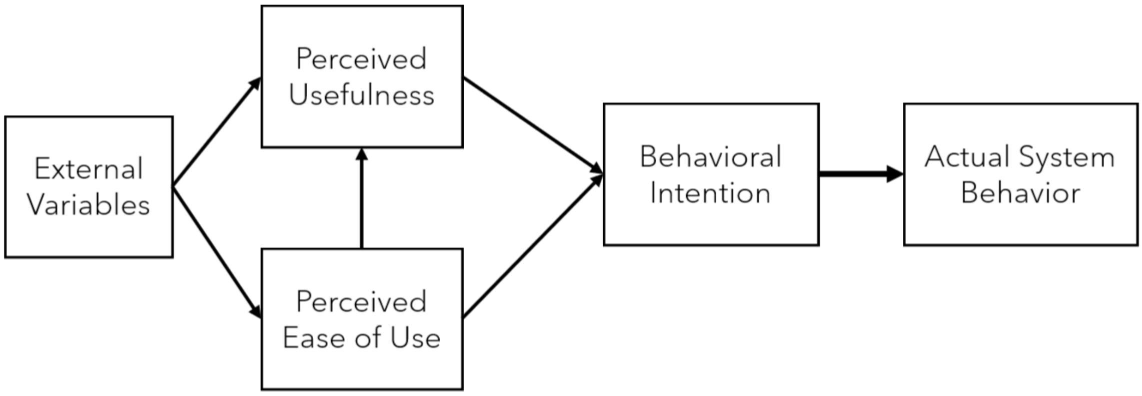

Figure 3.8. Revised Version of TAM Model

Source: Venkatesh & Davis, 1996

One significant advantage of the TAM is its framework for assessing the influence of external variables on the adoption of desired technologies (Hong et al., 2002). Numerous researchers have advocated for the inclusion of additional variables in the model to enhance its predictive capability. It is recommended that behavioral constructs and other external variables reflecting the user's task environment be integrated into the TAM to achieve this goal (Momani et al., 2017).

The technology acceptance model suggests that over time, as people gain more experience with the technology, they judge the usefulness of a system based on the potential situational benefits resulting from greater use of social information (Davis et al., 1989a). In other words, users pay attention to the formation of perceptual usefulness over time.

3.4.5. Technology Acceptance Theory 2 (TAM2)

While the TAM model has demonstrated its validity across various samples and contexts in explaining the acceptance and usage of information systems, many scholars have expanded the model in different forms. One notable extension is TAM Model 2, developed by Venkatesh and Davis (2000), which incorporates additional variables to explain how social norms and cognitive processes influence perceived usefulness and attitude.

In the TAM 2 model, external variables are specified to delineate their impact, while the concept of attitude is redefined. Unlike the basic TAM, where attitude emerges from beliefs about usefulness and ease of use, TAM 2 separates attitude as a distinct variable. This separation is based on the premise that both perceived usefulness and perceived ease of use independently contribute to forming attitudes toward technology acceptance (Figure 3.9.)

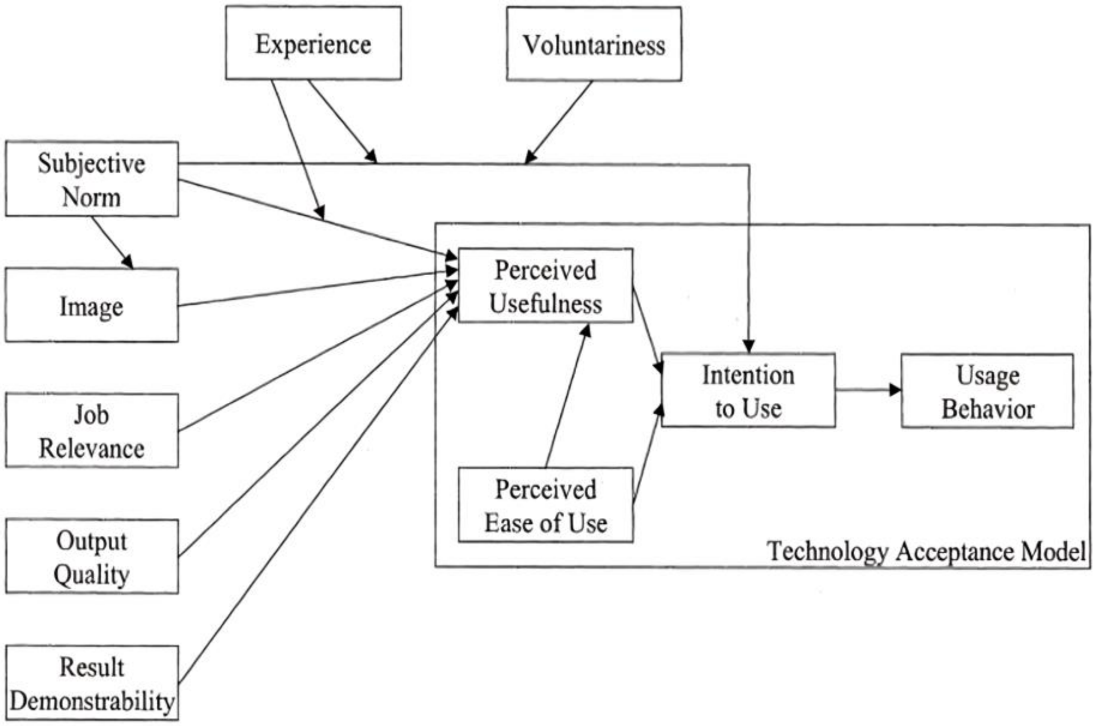

Figure 3.9. Technology Acceptance Model 2

Source: Venkatesh & Davis, 2000

In the TAM2 model, external variables such as social influences (subjective norm, image) and cognitive processes (job relevance, output quality, demonstrability, perceived ease of use) are specified, while the element of attitude has been omitted from the original model. The reason for removing the attitude is that understanding the perceived usefulness and perceived ease of use in the original model leads to the creation of a positive or negative attitude in the individual (Venkatesh & Davis, 1996). Therefore, in the secondary model of technology acceptance, where both factors exist and the presence of both is necessary to create an attitude, having a separate variable as attitude has been withdrawn.

In short, the TAM2 model tries to describe an individual's understanding of the usefulness of technology and the intention to use it in terms of social effects and cognitive processes. The model posits that the influence of social factors on perceived usefulness and usage intention diminishes as users gain experience over time (Venkatesh & Davis, 2000). TAM 2 model provides a more nuanced framework for understanding technology acceptance, integrating both social influences and cognitive processes to predict better user behavior in adopting new technologies.

3.4.6. The Unified Theory of Acceptance and Use of Technology

The Unified Theory of Acceptance and Use of Technology (UTAUT) is a comprehensive model developed by Venkatesh et al. (2003) that involves eight models: the theory of reasoned action (Fishbein & Ajzen, 1977), the Theory of Planned Behavior (Ajzen, 1985), Model of PC Utilization (Triandis, 1979), TAM 1 (Davis, 1989), a combined theory of planned behavior/technology acceptance model (S. Taylor & Todd, 1995a), Social Cognitive Theory (Bandura, 1989, 1999) , Motivational Model (Davis et al., 1992; Venkatesh & Speier, 1999) and, Innovation Diffusion Theory (Rogers, 1995). The goal of UTAUT is to understand users' intentions to utilize an information system and their subsequent behavior in using it. This model specifically explains individual's behaviors related to computer usage and various computer technologies (Lai, 2017).

In his study, Venkatesh conducted research involving employees from four organizations over a six-month period, with data collection at three distinct time points: immediate post-training, one month post-implementation, and three months post-implementation. The study measured actual usage behavior six months after training. Initial analyses using eight established models revealed that these models accounted for 17-53% of the variance in behavioral intention. Subsequently, Venkatesh tested the UTAUT using the collected data. The results demonstrated that UTAUT outperformed the other eight models, explaining 69% of the variance in intention to use technology (Venkatesh et al., 2003). This finding underscores the superior predictive capability of UTAUT in understanding technology acceptance compared to existing models.

The proposed framework in UTAUT suggests that there are four core determinants of technology adoption: expected performance, perceived ease of use, social influences, and supportive conditions (Figure 3.10.). The first three factors directly influence users' intentions to adopt and subsequent use of technology, while the latter primarily impacts actual usage. Individual characteristics such as gender, age, experience, and the voluntary nature of technology use may moderate the impact of these core factors on both adoption intentions and behavior (Venkatesh et al. 2003, p.447).

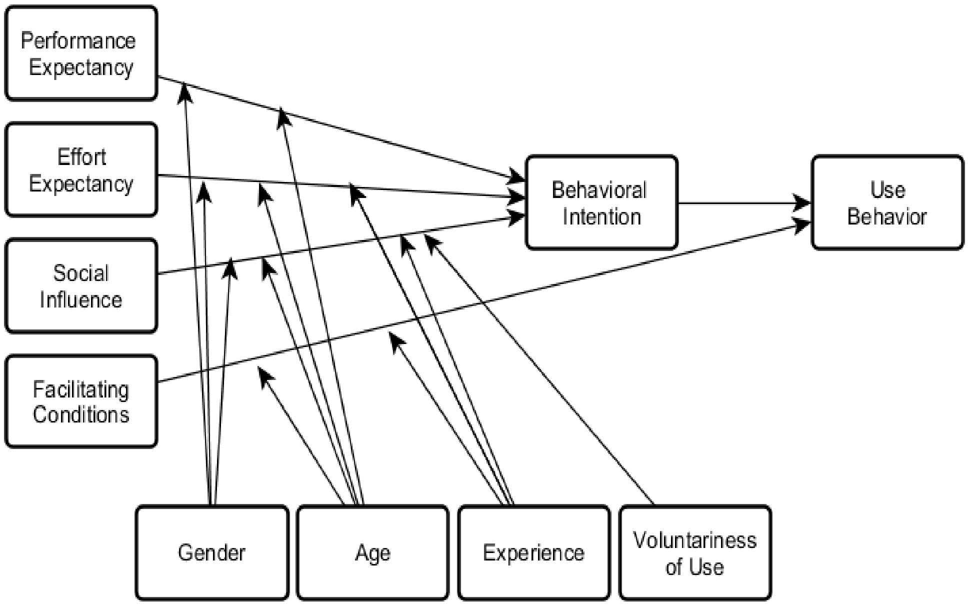

Figure 3.10. The Conceptual Framework for Unified Theory of Acceptance and Use of Technology (UTAUT)

Source: Venkatesh et al., 2003

3.4.7. The Unified Theory of Acceptance and Use of Technology 2 (UTAUT 2)

Nine years after the development of UTAUT, Venkatesh and his colleagues introduced UTAUT 2 model (Venkatesh, Thong, & Xu, 2012). UTAUT 2 is considered as one of the latest models of technology acceptance and use. This model, which is an advanced iteration of the UTAUT model, represents a significant advancement in understanding technology adoption. Building upon its predecessor, it offers enhanced explanatory power in predicting behavioral intention and actual technology usage. Specifically, UTAUT2 accounts for 74% of the variance in behavioral intention and 52% in technology use, surpassing the UTAUT model, which explains 56% and 60% of these respective variances. Therefore, this research adopts the UTAUT2 model to comprehensively investigate and understand behavioral intention and technology usage due to its superior explanatory capability.

The four original constructs were adopted from the original model, while hedonic motivation, price value, and habit were added to the model. Moreover, the moderating effects of age, gender, and experience were also included in the UTAUT 2 model (Figure 3.11)

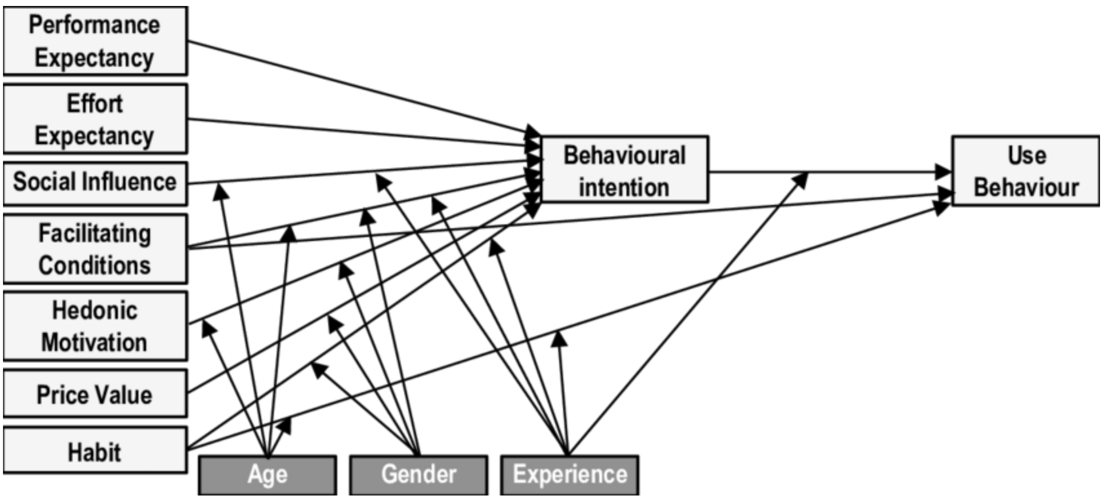

Figure 3.11. The Framework for UTAUT 2 Model

Source: Venkatesh, Thong, & Xu, 2012

Hedonic motivation refers to the pleasure and enjoyment derived from the experience of using a product or service. It encapsulates the emotional and sensory gratification that individuals perceive while interacting with the product. This aspect of motivation emphasizes the intrinsic rewards and satisfaction gained from the product's features, design, or overall user experience (Venkatesh, Thong, & Xu, 2012).

Price value represents the perceived balance between the cost of acquiring a product or service and the benefits derived from its use. It reflects consumers' judgments regarding whether the product's utility justifies its price tag, considering factors such as quality, functionality, and perceived value for money. This evaluation is crucial in influencing consumers' purchase decisions and their willingness to pay for a particular product or service (A. Chang, 2012).

Habit denotes the automatic and ingrained performance of a behavior due to repeated exposure and learning over time. It involves the subconscious execution of actions without deliberate decision-making or conscious intent. Habits develop through consistent repetition of behaviors, which create mental associations and routines that streamline actions in familiar contexts (Tamilmani et al., 2021).

3.5. Service Quality Scale (SERVQUAL)

The SERVQUAL scale, developed by Parasuraman, Berry, and Zeithaml, stands as a renowned approach for assessing service quality. Originating from their work initiated in 1983, the project to measure service quality was endorsed by the American Marketing Science Institute (Grapentine, 1998). By 1985, the researchers had validated their findings across various service sectors, including banking, insurance, credit cards, telecommunications, maintenance, security brokers, and road transportation companies (Parasuraman et al., 1990).

The body of knowledge surrounding service quality has evolved continuously, benefiting from the cumulative research and insights of scholars. Early contributions by Grönroos (1984) established a basis for understanding service quality measurement. Grönroos noted that word-of-mouth marketing exerts a significant influence on potential customers in contrast to traditional marketing efforts. In addition, he noted that the need for service quality is based on consumer observations (Grönroos, 1984). Later, the Grönroos model was referred to as a European perspective of the SERVQUAL among scholars (Kang & James, 2004).

In 1985, Parasuraman and his colleagues conceptualized service quality by defining it as the difference (gaps) between customer expectations and perceptions across various levels (Mukhtar et al., 2017). They introduced five gaps (Figure 3.12) which are as follows: Consumer expectation-management perception gap (GAP 1): The difference between management's perceptions of what customers expect and actual customer expectations. Management perception-service quality specification gap (GAP 2): Difference between management perceptions and service quality specifications (service quality standards). Service quality specifications-service delivery gap (GAP 3): the difference between service quality specifications and actual service delivery. Service delivery-external communications gap (GAP 4): the difference between service delivery and what is desired outside the organization. Expected service-perceived service gap (GAP 5): the difference between what customers expect from a service and what they actually receive (Parasuraman et al., 1985).

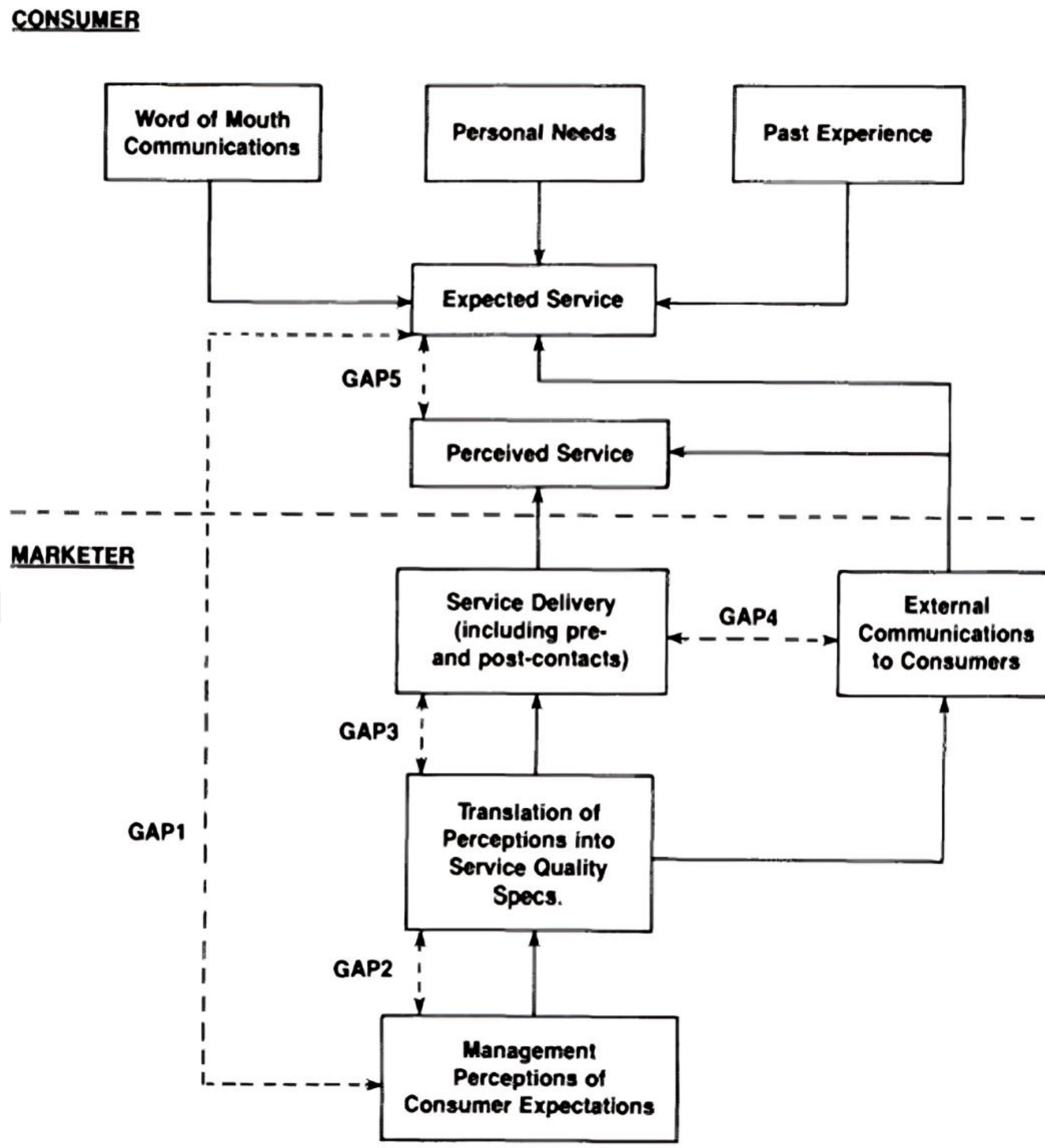

Figure 3.12. Service Quality Model

Source: Parasuraman et al., 1985

Parasuraman and his colleges (1985) stated that the foundation of SERVQUAL is the set of mentioned gaps. They also mentioned that the main gap is expected service-perceived service gap and all other gaps are function of GAP 5 (Parasuraman et al., 1985).

In addition, ten dimensions for SERVQUAL were introduced (Figure 3.13) tangibility, reliability, responsiveness, competence, courtesy/respect, credibility, security, access, communication, and being customer-oriented (Parasuraman et al., 1985).

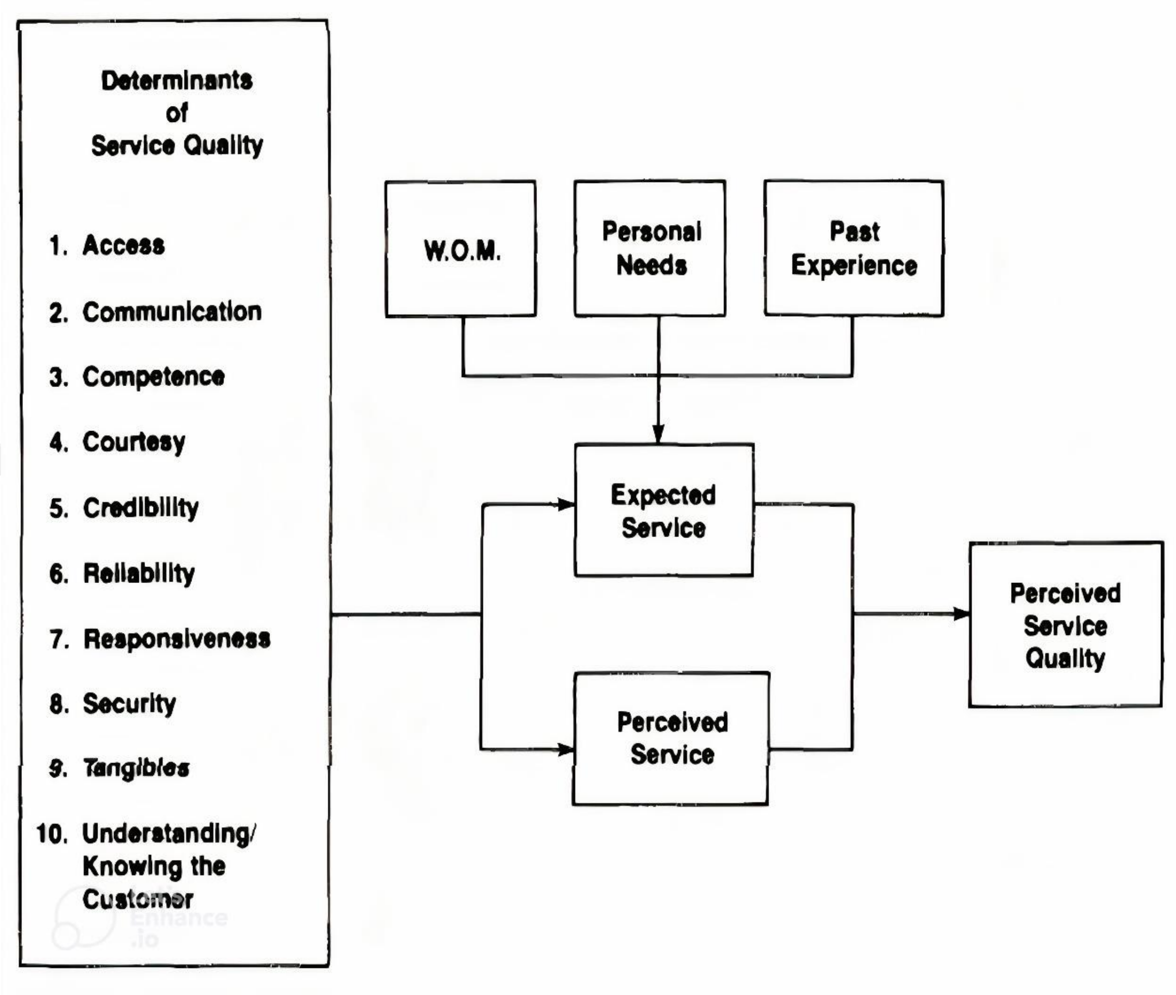

Figure 3.13. Ten Determinants of SERVQUAL

Source: Parasuraman et al., 1985

Later, Parasuraman and his colleagues reduced the mentioned ten factors to five factors known as RATER, which stands for reliability, assurance, tangibility (physical facilities and appearance), empathy, and responsiveness (Parasuraman et al., 1990).

3.6. Criticism of SERVQUAL and Its Alternatives

Despite its success and popularity, SERVQUAL received different criticism from many researchers. Cronin and Taylor (1992) criticized the difficulty level for the process of data collection and having a biased response in SERVQUAL. As a result, they proposed SERVPERF, standing for service performance, in which only perceived perception was evaluated. They claimed that the validity and reliability of SERVPERF is higher than SERVQUAL in addition to having higher adjusted R^2 and explained variance (Cronin Jr & Taylor, 1992).

Kang and James (2004) argued that SERVQUAL only reflects the service delivery process and lacks concentration on functional quality dimensions. They suggested Grönroos' model consisting of three dimensions of technical, functional, and image for overcoming these limitations. On the same line, Asubonteng, McCleary, and Swan (1996) criticized SERVQUAL for its dimensionality and existing interdependency between variables. Mangold and Babakus (1991) also criticized SERVQUAL for focusing only on the service delivery process, not the service outcome. In addition, they argued that SERVQUAL is not adequate for covering a wide range of services in different sectors, and each service type requires its own scale for evaluation. Cronin and Taylor (1992)

Consequently, different scales within the same framework started to appear in other scholars for various types of services. Some examples that cover topics related to human and computer interaction are as follows: SITEQUAL for shopping sites (Z. Yang et al., 2003), WebQual for website quality measurement (Salomi et al., 2002), E-S-Qual for online shopping (Parasuraman et al., 2005) and, PeSQ for internet service quality (Cristobal et al., 2007).

3.7. SSTQUAL

Based on the literature for SERVQUAL and other alternatives, it can be stated that they are intended to recognize the connection between customers and employees/firms, but they do not completely encompass customer self-service technology interactions (Lin & Hsieh, 2011). As a result, this gap led to the development of the 'SSTQUAL' scale by Lin and Hsieh (2011) to address the various dimensions of self-service technology service quality.

Lin and Hsieh (2011) initially developed a scale with 75 items, which was reduced to 27 items following expert consultation and rigorous refinement using component analysis and varimax rotation. Finally, they introduced a seven-dimensional scale with 20 measuring items. These seven dimensions are as follows: functionality, enjoyment, security, assurance, design, convenience, and customization (Figure 3.14).

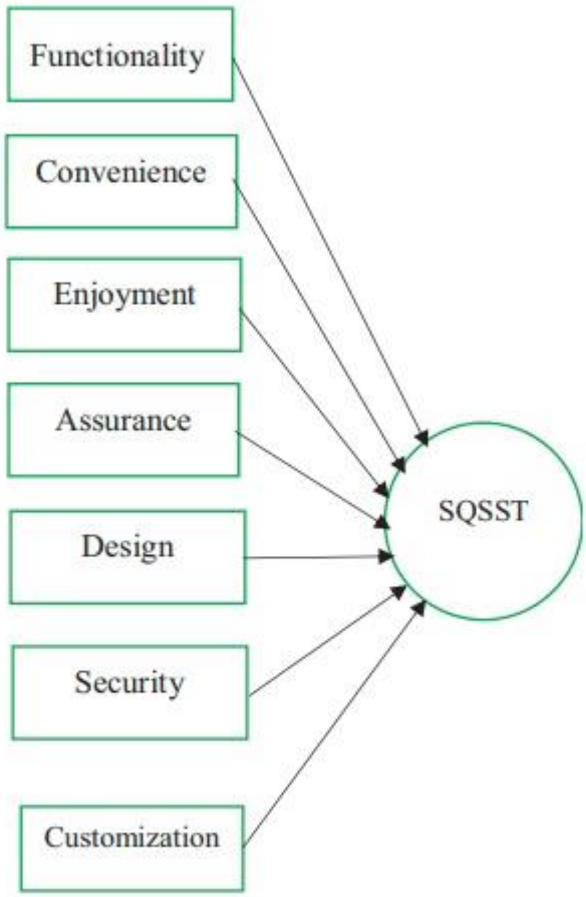

Figure 3.14. Seven Dimensions for SSTQUAL

Source: Ghosh, 2021

In their proposed model, Lin and Hsieh (2011) merged three variables from the original SERVQUAL (responsiveness, reliability, and ease of use) into a single dimension called functionality. In their original paper, they define other dimensions as follows: Enjoyment is defined as the perception of enjoyment perceived by customers while using SST. The security/privacy dimension describes perceptions of safety from fraud, intrusion, and privacy violation. Assurance refers to confidence projected from the reputation and capability of the SST provider. Design refers to the overall design and layout of the SST service system, encompassing elements such as interface usability, technological integration, and user experience considerations. Convenience is related to the ease of access and usability of SST services, emphasizing how readily available and user-friendly the self-service options are for customers. It encompasses factors such as location, availability, and the efficiency with which users can navigate and utilize the services offered by SST systems. Finally, Customization reflects the extent to which an SST can be tailored to accommodate individual customer preferences. It highlights the flexibility and adaptability of self-service technologies in personalizing the user experience based on specific needs and past interactions (Ghosh, 2021).

3.8. Integration of Service Quality into Models for Technology Acceptance

Upon the adoption of SERVQUAL by scholars, studies exploring the effect of service quality on theoretical models of technology acceptance emerged (Cao et al., 2005). This development opened new doors to investigations into how perceptions of service quality influence user acceptance and adoption of technological innovations across various domains.

The majority of these studies used the technology acceptance model (TAM) as their backbone (M. Y. Chang et al., 2015; Jang & Noh, 2011). Furthermore, none of these studies incorporated dimensions from SERVQUAL or other service quality measurement scales. Instead, they focused on examining the significant relationship between service quality and the main factors of the TAM models. This approach could potentially lead to a less comprehensive understanding of the factors that affect users' perceptions and behaviors toward new technologies by overlooking nuanced aspects of service quality that could influence technology acceptance (Malanga et al., 2022).

Therefore, recent research has proposed extending technology acceptance models by incorporating relevant dimensions from service quality frameworks. This integration acknowledges the interconnectedness between service quality and technology acceptance, thereby enhancing the applicability and explanatory power of theoretical frameworks in studying user behavior in technological contexts (Legramante et al., 2023; Malanga et al., 2022).

3.9. Hypothesis Development

In the light of the provided discussion, this dissertation proposed a model that combines one of the latest theoretical models for technology acceptance, UTAUT 2 (Venkatesh, Thong, & Xu, 2012), with the SSTQUAL model (Lin & Hsieh, 2011), which is specifically designed for measuring service quality of self-service technologies.

3.9.1. Performance Expectancy

According to Venkatesh and his colleagues (2012), performance expectancy is defined as the extent to which a person believes that using this system will help him gain benefits in doing the job. It is derived from following five constructs that are related to performance expectations: usefulness from TAM/TAM2 (Davis, 1989; Venkatesh & Davis, 2000) and combined TAM and Theory of Planned Behavior (S. Taylor & Todd, 1995a), extrinsic motivation from Motivational Model (Davis et al., 1992; Venkatesh & Speier, 1999), job fit from Model of PC Utilization (Triandis, 1979), relative advantage from diffusion of innovation theory (Rogers, 1995), and output expectations from Social Cognitive Theory (Bandura, 1989).

The construct of performance expectation within each individual model emerges as the most robust predictor of willingness, maintaining significance across all measurement points in both mandatory and voluntary conditions (Venkatesh et al., 2003). Venkatesh et al.'s (2003) findings corroborate with the previous model (Agarwal & Prasad, 1998; Davis, 1989; S. Taylor & Todd, 1995a; Venkatesh & Davis, 2000). Based on the literature and provided discussion, this study proposes the following hypothesis:

H_1: *Performance Expectancy of passengers regarding SCKs will have a positive direct effect on behavioral intention.*

3.9.2. Effort Expectancy

Similar to performance expectancy, effort expectancy is considered as a core construct within the UTAUT 2 model. It is related to an individual's belief regarding the level of effort required to use a particular technology. Essentially, it measures the perceived ease or difficulty of using a system (Venkatesh et al., 2003). Effort expectancy is defined as the degree of ease associated with using the system (Venkatesh, Thong, & Xu, 2012). Three constructs from previous models capture the concept of effort expectancy: perceived ease of use (TAM/TAM2), complexity (Model of PC Utilization), and ease of use (Diffusion of Innovation Theory).

When users believe that a technology is easy to use and requires minimal cognitive effort, they are more likely to adopt and utilize it (Momani & Jamous, 2017). Conversely, if users perceive a technology as complex or demanding, their intention to use it decreases. Positive effort expectancy empowers users with a sense of control over their actions and the technology they use, motivating them to explore its functionalities (A. Chang, 2012). On the other hand, when the perceived effort is high, it can create feelings of frustration and anxiety, potentially resulting in reluctance to interact with the technology (Tarhini et al., 2019). In addition, previous studies suggest that effort expectancy has a significant effect on the performance expectancy of the users toward the technology (Rahi et al., 2019; Tannady & Dewi, 2024). Accordingly, the following hypothesis will be tested for this study:

H$_2$: *Effort Expectancy of passengers regarding SCKs will have a positive direct effect on behavioral intention.*

H$_3$: *Effort Expectancy will have a positive direct effect on the performance expectancy of passengers.*

3.9.3. Hedonic Motivation

Hedonic motivation is defined as the pursuit of pleasure and fun derived from technology use (Venkatesh, Thong, & Xu, 2012). This construct has been shown as a pivotal determinant of technology acceptance within the Information Systems (IS) domain (Chiu et al., 2009). This construct has been consistently found to profoundly influence individuals' decisions regarding the adoption and continued use of technological innovations (Legramante et al., 2023). The pleasurable experiences afforded by technology are believed to foster positive attitudes, enhance user satisfaction, and ultimately drive technology acceptance (Thong et al., 2006). Thus, the following hypothesis is proposed:

H_4: *Hedonic Motivation will have a positive direct effect on the behavioral intention of passengers toward SCKs.*

3.9.4. Social Influence

Social influence is defined as the degree to which an individual perceives that others, such as family members, colleagues, or influential figures, hold expectations regarding their adoption and utilization of technology (Venkatesh, Thong, & Xu, 2012). This perception encompasses the social pressures, norms, or expectations perceived by the individual, influencing their decision-making process regarding technology adoption (Chiu et al., 2009; Legramante et al., 2023).

This construct serves as a direct determinant of behavioral intention across various theoretical frameworks such as the Theory of Reasoned Action, Technology, TAM2, Theory of Planned Behavior, Diffusion of Innovations Theory of Planned Behavior. This construct, while variously labeled as subjective norms, social factors, or images within different models (Momani & Jamous, 2017), underscores the principle that individuals' technology adoption decisions are influenced by their perceptions of social approval or disapproval. Despite the differing labels, each of these constructs posits that individuals' behaviors are influenced by their perceptions of how others will view them based on their adoption of the technology. Accordingly, the following hypothesis will be tested for this study:

H_5: *Social Influence will have a positive direct effect on the behavioral intention of passengers toward SCKs.*

3.9.5. Facilitating Condition

Facilitating conditions refer to an individual's perception of the organizational and technical support available to use a system effectively (Venkatesh, Thong, & Xu, 2012). This definition includes concepts expressed by three different constructs from previous models: perceived behavioral control from combined TAM and Theory of Planned Behavior (S. Taylor & Todd, 1995a), facilitating conditions from the model of PC Utilization (Triandis, 1979), and adaptability from diffusion of innovation theory (Rogers, 1995). Taylor and Todd (1995b) confirmed that there is a theoretical fit with modeling facilitating conditions as a central component for perceived behavioral control. The compatibility construct derived from IDT incorporates items that align with individual work styles and the organizational use of the technology. This construct focuses on practical factors within the technical and organizational environment to eliminate obstacles for users.

According to some scholars, facilitating conditions is crucial to understanding the practical aspects that can either facilitate or hinder technology adoption within organizational settings (Hossain et al., 2017; Venkatesh et al., 2008; Yuan et al., 2023). Organizational facilitators include the availability of technical support personnel, training programs tailored to the system's functionalities, clear policies and procedures regarding system use, and compatibility with existing infrastructure (Venkatesh, Thong, & Xu, 2012).

The mentioned factors collectively enhance users' confidence and competence in utilizing the technology, fostering positive attitudes and intentions toward its adoption (Hossain et al., 2017). In addition, perceptions of adequate technical infrastructure, access to training and support personnel, and the compatibility of the new technology with existing systems all contribute to facilitating conditions (Ambarwati et al., 2020). Accordingly, the following hypothesis is proposed for facilitating condition:

H_6: *Facilitating Condition will have a positive direct effect on the behavioral intention of passengers toward SCKs.*

3.9.6. Functionality

Functionality refers to a technology or system's inherent capabilities and features that address users' needs and objectives (Ghosh, 2021). This construct encompasses the technology's responsiveness, practical utility, ease of use, and effectiveness in accomplishing specific tasks and achieving desired outcomes. A technology's functionality directly impacts its perceived usefulness, a key driver of technology acceptance (Lin & Hsieh, 2011). When a technology offers a robust and user-friendly set of features that effectively address user needs, it is more likely to be adopted and used regularly (Radomir & Nistor, 2012).

Previous studies showed that the impact of functionality on users' behavioral intention to adopt and use new technology is profound and significant (Abdul Wahab, 2011; Maio & Olson, 1995; Singh, 2018). Users evaluate functionality based on a technology's ability to efficiently and effectively address their needs. A system with strong functionality featuring intuitive interfaces, comprehensive features, and seamless integration with existing tools encourages favorable perceptions of its usefulness and importance (Lin & Hsieh, 2011). Such positive evaluation translates into believing that the technology can meet operational requirements, ultimately increasing users' motivation to adopt it. Consequently, the following hypothesis is proposed:

H_7: *Functionality will have a positive direct effect on the behavioral intention of passengers toward SCKs.*

3.9.7. Assurance

Assurance refers to the user's confidence level in the technology provider of SST (Lin & Hsieh, 2011). This confidence is often shaped by users' past experiences with similar technology providers (Keh & Xie, 2009). Additionally, perceptions of the technology provider can be influenced by word-of-mouth recommendations and shared experiences among users regarding their interactions with the organization.

Users' assurance in the technology provider is crucial as it directly impacts their trust and willingness to engage with technology (Corkindale & Belder, 2009). Positive past experiences contribute to a higher level of assurance, while negative encounters may lead to skepticism or reluctance (Lin & Hsieh, 2011). Similarly, when users hear positive feedback from peers or encounter favorable reviews, it enhances their perception of the provider's reliability and credibility (Yoo et al., 2010). This social validation can significantly shape users' attitudes and behaviors towards adopting and using new technology. As a result, the below hypothesis is proposed to be tested:

H_8: *Assurance will have a positive direct effect on the behavioral intention of passengers toward SCKs.*

3.9.8. Security/Privacy

Security and privacy refer to the perceived level of protection against unauthorized access, fraudulent activities, and the potential compromise of personal information (Lin & Hsieh, 2011). This concept encompasses the measures and safeguards put in place to ensure the safety and confidentiality of data in various contexts, such as digital transactions and information storage systems (Harborth et al., 2020). Studies suggest that factors such as perceived anonymity strongly influence trust in the interaction with new technology, and trust significantly affects behavioral intention (Harborth et al., 2020). Using the UTAUT 2 Model, Alharbi and his colleagues (2017) found that security perception strongly influences trust, which eventually significantly affects the intention to use digital platforms (Alharbi et al., 2017). Siagian et al. (20022) came to similar conclusions by using the TAM model. They found that perceived security has a positive significant effect on users' behavioral intention for digital payment through social media platforms (Siagian et al., 2022).

As a result, this study proposes the following hypothesis related to security/privacy and behavioral intention:

H_9: *Security will have a positive direct effect on the behavioral intention of passengers toward SCKs.*

3.9.9. Enjoyment

Perceived enjoyment refers to the perception of enjoyment experienced while using SST and while receiving outcomes (Song & Han, 2009). Although the provided definition for this construct is paralleled to hedonic motivation, the measuring items in SSTQUAL focus on positive feelings that the user may experience through receiving additional features, functions, and information that may be acquired by using the SST (Lin & Hsieh, 2011). Previous research indicates that integrating additional or bonus features into products or services, which blend functional utility with entertainment value, can significantly enhance customers' behavioral intentions toward using the technology (Basuki et al., 2022; Teo & Noyes, 2011). These enhanced features not only fulfill practical needs but also appeal to emotional and experiential aspects, which can enrich the overall user experience. Therefore, the following hypothesis is proposed regarding enjoyment:

H_{10}: *Enjoyment will have a positive direct effect on the behavioral intention of passengers toward SCKs.*

3.9.10. Perceived Risk

Perceived risk refers to an individual's apprehension about the potential negative consequences associated with adopting new technology (Torki Biucky et al., 2017). These consequences can be financial (Liebermann & Stashevsky, 2002), social by the means of embarrassment if the technology malfunctions publicly (Lovreglio et al., 2016), or performance-related, which can be related to fear of appearing incompetent due to difficulty using the technology (Lee & Song, 2013). This complex perception of risk can serve as a significant obstacle to user adoption, hindering the spread and achievement of new technologies.

When people view technology as risky, they tend to show what Ajzen (1991) referred to as a "negative behavioral intention," meaning that they are hesitant to embrace the new technology or choose to delay its adoption. This behavior arises from a concern about potential negative outcomes linked to the perceived risk. Individuals may choose to delay adoption completely, relying on traditional or familiar options, or they may engage in a cautious and limited trial period before committing to full use. This study proposes the following hypothesis regarding the perceived risk:

H10: *Perceived risk will negatively moderates the positive relationship between behavioral intention and use behaviour such that increased perceived risk weakness the relationship.*

3.10. Conceptual Framework

By adopting variables from both the UTAUT 2 model and SSTQUAL, we proposed the following framework (Figure 3.15) for testing the stated hypotheses for this dissertation.

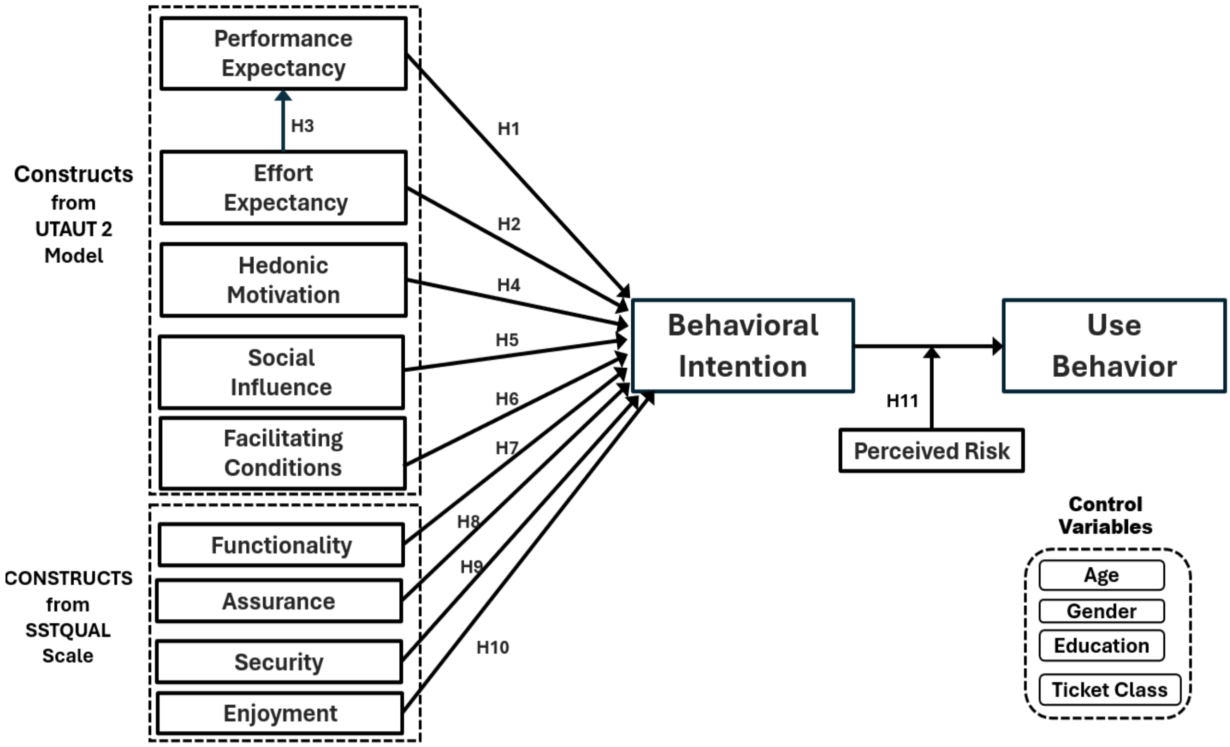

Figure 3.15. Proposed Conceptual Framework

CHAPTER IV

RESEARCH METHODOLOGY

This chapter discusses the methodology and approaches selected for testing the proposed hypothesis in this dissertation. It starts with an overview of this study's research philosophy and proposed frameworks.

4.1. Research and Framework

In order to follow a transparent and well-established research design, this dissertation adopts the concept of research onion (Figure 4.1).

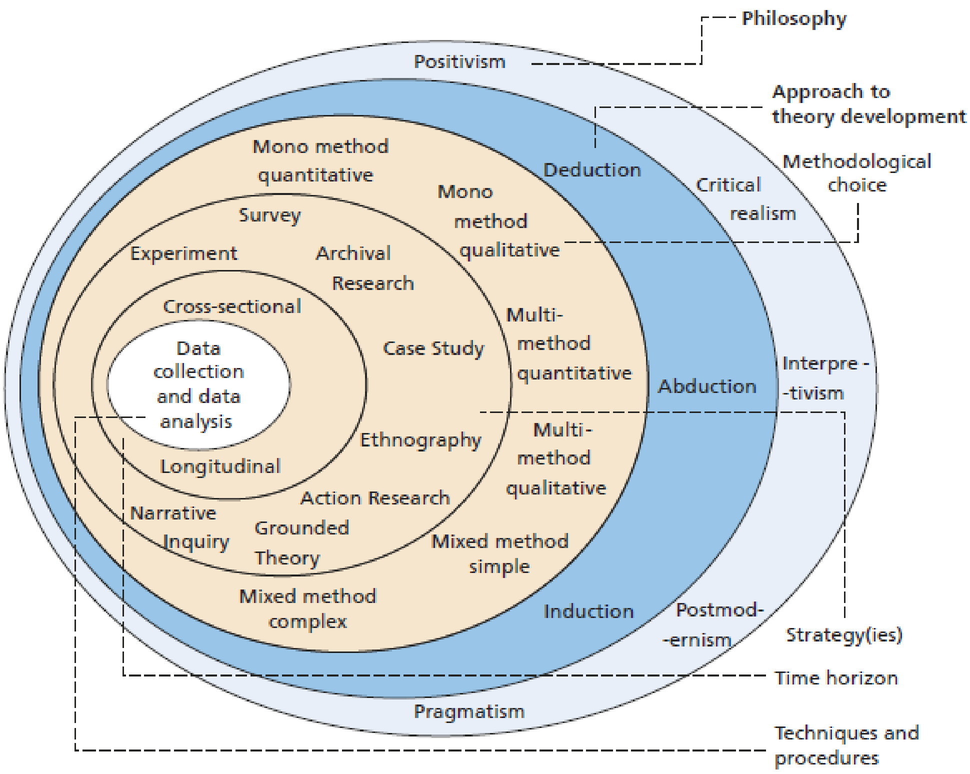

Figure 4.1. The Research Onion

Source: Saunders et al., 2009

This concept was first introduced by Saunders, Lewis, and Thornhill (2009) in their book titled " Research Methods for Business Students". Research onion is a metaphorical framework that aims to help researchers develop and organize a complex research path. It provides a structured approach to designing and conducting research, starting from the outermost layer (philosophy) down to the innermost layer (data collection and analysis methods).

4.1.1. Research Philosophy

The first layer of any scientific research has been introduced to know the research philosophy. Research philosophy serves as the initial gateway in any scientific investigation, offering insights into the methodology and epistemological stance taken by researchers (Crossan, 2003). In a simple definition, research philosophy, also sometimes called research paradigm, refers to a set of assumptions, beliefs, and principles that underline research.

Research philosophy in business and management sciences includes the following five categories (Saunders et al., 2019, pp.144-155):

- **Rationalism** is based on the power of thinking and the basic assumption that reason is capable of knowing all phenomena. Ancient philosophers from Plato and Aristotle to René Descartes followed this view (Crossan, 2003).

- **Positivism** is based on the principles of experimental science and the objective approach. Positivism assumes that reality is something that an individual can experience through the senses. This philosophical approach is suitable for deductive reasoning and quantitative research (Saunders et al., 2019).

- **Postmodernism** focuses on the role of language and power dynamics, aiming to challenge established modes of thought and promote alternative perspectives that have been ignored.

- **Pragmatism** emphasizes the practical consequences of knowledge rather than seeking absolute truth. This philosophical approach is suitable for mixed research.

- **Interpretivism** is based on a subjective approach. That is, it is assumed that reality is not objective and is subjective and socially constructed.

- **Critical realism** is based on a dialectical approach and the challenges of positivist philosophy. According to this philosophical approach, "reality" cannot be observed. Reality is independent of human understanding, theorizing, and abstractions.

Based on the above discussion and also the objectives and research questions stated in Section 1.3, this dissertation selects a positivist philosophy for the study. As a reminder, this dissertation aims to provide a casual explanation and prediction of a phenomenon (factors affecting BI of passengers toward SCKs) through observable and measurable facts (survey and data analysis). As a result, the positivism philosophy is best-suited for testing the proposed hypothesis of this study.

4.1.2. Research Approach

Three primary research approaches guide theory development: induction, deduction, and abduction (Saunders, Lewis, and Thornhill 2019, 152).

- **Induction** involves the bottom-up development of theory from empirical observations. Researchers gather data, identify patterns, and progressively refine these patterns into a theory that explains the observed phenomena.
- **Deduction** adopts a top-down approach. Researchers begin with established theories or hypotheses and then test their predictions through data collection and analysis.
- **Abduction** represents a more iterative approach, drawing on both induction and deduction. The researcher would move back and forth between the observation and theory.

This dissertation employs a deductive approach for the following reasons. First, the proposed hypothesis of the study is formed based on previous studies and available theories. The UTAUT 2 model is developed by combining multiple theories for technology acceptance and human psychology. Similarly, SSTQUAL is considered a multidimensional model for evaluating the service quality of self-service technologies. Next, both models (UTAUT 2 and SSTQUAL) have been tested for various industries in numerous studies in the past (Ghosh, 2021; Momani & Jamous, 2017), and the obtained results in many studies were consistent with previous ones. Finally, the quantitative method will be used for accepting or rejecting the proposed hypothesis. All the mentioned points are consistent with the deductive approach (Bhandari, 2023) (Figure 4.2) As a result, this study will follow the deductive approach for its path.

Figure 4.2. Deductive Reasoning

Source: (Bhandari, 2023)

4.1.3. Methodological Choice

Broadly speaking, research methods can be divided into quantitative and qualitative, each with different techniques and instruments (Saunders et al., 2019). Understanding the two types is essential before selecting the most appropriate research technique. Quantitative research deals with numbers and graphs in order to test or confirm theories and hypotheses. It relies on methods such as observations and surveys with closed-ended questions to gather measurable data (Azungah, 2018).

Alternatively, qualitative research primarily relies on text, words and descriptions in order to explore concepts and phenomena. It allows researchers to explore deeply into complex and ambiguous subjects that are hard to understand in general. Qualitative data collection methods include interviews with open-ended questions, observations that are described in words, and literature reviews that examine concepts and theories (Crossan, 2003).

Considering the characteristics of both approaches and the study's positivist philosophy and deductive reasoning, the quantitative approach seems appropriate for the research design. In addition, since the research is focused on quantitative data gathering (survey data collection), the mono-method quantitative method explicitly describes the methodological choice of this dissertation.

4.1.4. Research Strategy

This dissertation uses surveys to collect data needed for the study. Surveys are typically employed to gather data for quantitative studies from a sample that represents the study's target population (Saunders et al., 2019). The collected data was subsequently analyzed through empirical methods.

4.1.5. Time Horizon

The cross-sectional data for this dissertation was collected in two phases: The summer of 2023 and the spring of 2024. Six visits on separate dates were made. Three visits belonged to Istanbul Grand Airport, and three visits belonged to Istanbul Sabiha Gökçen International Airport. The researcher collected the data by hand on each visit from passengers who were available to participate in the study. The reason for distributing surveys face-to-face and by hand was to increase the accuracy and reliability of the data (Taherdoost, 2021).

4.1.6. Data Analysis Tools and Techniques

In order to test the proposed model and its hypotheses, this dissertation employed the Structural Equation Modeling (SEM) technique. SEM is a powerful multivariate statistical technique that enables researchers to investigate complex causal relationships among latent and observed variables. It goes beyond traditional regression by estimating both direct and indirect effects while simultaneously accounting for measurement error (Grunst et al., 2022).

In addition, two statistical analysis software were used to analyze the collected data: IBM SPSS 27 and SmartPLS 4. SPSS was used to sort, clean, and conduct descriptive and initial factor analysis whereas SmartPLS was used to conduct the confirmatory factor analysis (CFA) and path analysis in the structural model. In addition, all the reliability, validity, and model fit analyses were conducted with the SmartPLS software.

4.2. Population and Sampling

4.2.1. Population

A statistical population is a set of people or units that have at least one common attribute (Saunders et al., 2019). Sekaran and Bougie (2016) describe the population as a set of groups, individuals, objects, or events that are the focus of the research. Basically, the population of a study is defined by specific characteristics or criteria that are relevant to the research questions and objectives of the study being conducted. The target population for this study is set to be passengers who are over 18 years of age with any educational background and have been traveling via the IGA or ISG airports. Another critical criteria was that the participant should be familiar with kiosks or at least have a general knowledge about them.

There are no statistics for the number of passengers with the exact mentioned criteria; however, we consider the total number of passengers traveling with IGA and ISG airports as the population of this study. According to the official website of the Sabiha Gökçen International Airport (www.sabihagokcen.aero), the total passenger number (including domestic and international passengers) for 2023 was more than 37 million (ISG, 2024). Istanbul Airport (IGA) nearly doubles this figure, boasting over 76 million passengers (Gill, 2024).

4.2.2. Sample Size

A sample of a population refers to a smaller group selected from the population. Basically, researchers select a sample with the aim of studying it and drawing inferences about the entire population (Sekaran & Bougie, 2016). Selecting a sample requires ensuring that it is representative of the study's population so that what is learned from the sample can be generalized back to the population with a reasonable degree of assurance, known as confidence level (Saunders et al., 2009). Different sampling techniques are available suited to different research objectives and population characteristics, ensuring that the sample accurately represents the diversity and characteristics of the sampled population.

Determining the sample size and estimating the required number of samples that represent the characteristics of a statistical population is one of the crucial topics of the research method. Cochran's formula (0.1) is traditionally used for this purpose where n_0 is the sample size, Z is the z value extracted from z-table, e is the margin of error, p is the population size, and q is equal to 1-p (Cochran, 1977).

$$n_0 = \frac{Z^2pq}{e^2} \qquad 0.1)$$

Krejcie and Morgan (1970) developed a table, which was later referred to as Morgan’s table (Table 4.1), in which they calculated the sample size for different population sizes with a margin error of 5 % (Krejcie & Morgan, 1970). It should be noted that for populations (N) of 1,000,000 and more, the sample size (S) is set at 384.

Table 4.1 Morgan Table: Required Sample Size for Given Population

N	S	N	S	N	S	N	S	N	S
10	10	100	80	280	162	800	260	2800	388
15	14	110	86	290	165	850	265	3000	341
20	19	120	92	300	169	900	269	3500	346
25	24	130	97	320	175	950	274	400	351
30	28	140	103	340	181	1000	278	4500	354
35	32	150	108	360	186	1100	285	5000	357
40	36	160	113	380	191	1200	291	6000	361
45	40	170	118	400	196	1300	297	7000	364
50	44	180	123	420	201	1400	302	8000	367
55	48	190	127	440	205	1500	306	9000	368
60	52	200	132	460	210	1600	310	10000	370
65	56	210	136	480	214	1700	313	15000	375
70	59	220	140	500	217	1800	317	20000	377
75	63	230	144	550	226	1900	320	30000	379
80	66	240	148	600	234	2000	322	40000	380
85	70	250	152	650	242	2200	327	50000	381
90	73	260	155	700	248	2400	331	75000	382
95	76	270	159	750	254	2600	335	1000000	384

Krejcie and Morgan, (1970)

There are various opinions when it comes to determining an appropriate sample size for Structural Equation Modeling (SEM) (Memon et al., 2020). While some scholars suggest that even relatively small samples can yield meaningful results for simple SEM models (Hoyle, 1999), most research recommends a minimum of 100-150 participants (Anderson & Gerbing, 1988; Kline, 2023). The suggested minimum sample size for more complex models can increase to 200 (Boomsma & Hoogland, 2001; Kline, 2023). Notably, studies with ideal data conditions, meaning having normally distributed variables and no missing data, suggest a sample size of around 150 for basic Confirmatory Factor Analysis (CFA) models (Muthén & Satorra, 1995). Barclay et al., (1995) suggested that the sample size for SEM analysis should be equal to 10 times the number of formative indicators used for measuring constructs.

By looking at previous studies that conducted SEM analysis for airport passengers, we may get a better understanding of the correct sample size. Most of these research selected a sample size ranging from 300 to 450 (Bogicevic et al., 2017; Lu et al., 2009; Pholsook et al., 2023). For instance, Kim and Park (2019) tested their hypotheses using SEM for 400 participants to analyze the effect of SST characteristics on airport passengers. Using a TAM model, Ku and Chen (2013) conducted a SEM analysis among 429 passengers at Twainian airport. They investigated how service process fit and facilitating conditions affect the usage behavior of SSTs. Similarly, Taufik and Hanafiah (2019) studied the factors affecting passenger adoption and behavior of self-service technology (SST) in airports for 384 passengers.

Based on the early discussion regarding different methods for selecting sample size and the previous studies mentioned above, this study set its sample size as 400 participants.

4.2.3. Sampling Technique

This dissertation employed sampling technique which is a mix of simple random and convenience sampling, meaning that the researcher randomly approached potential participants in the selected airports to see if they were willing to participate in the study. Upon their approval, researchers provided general information about Self-Service Check-In kiosks (SCKs) to assess participants' familiarity with these systems.

Based on the participants' general knowledge regarding kiosks, the researcher decided to include them in the study.

4.3. Survey Design

In order to collect the required data, this study selected the survey as its instrument. The designed survey included three sections. The first section is the cover page and consent form (Figure 4.3). It aims to introduce the researcher, his affiliation, research objectives, and general information regarding self-check-in kiosks in airports to evaluate participants' familiarity level. In addition, it assures participants that the study will be conducted anonymously and no personal information will be collected.

PARTICIPANT INFORMATION AND CONSENT FORM

Dear Participant,

We invite you to participate in research titled "Check-in Kiosks at Airports". Before you decide whether to participate in this research, you need to know why and how the research will be conducted. Therefore, it is of great importance to read and understand this form. Take the time to read the information below carefully. If you wish, discuss this informationwith your family and/or relatives. If there are things you do not understand or are not clear to you, or if you would likemore information, ask us.

Participating in this survey is entirely voluntary. You have the right not to participate in the study. Your answering of the survey will be interpreted as your consent to participate in the research. Do not be under anyone's pressure or suggestions when answering the questions in the survey forms given to you. The information obtained from these forms will be used entirely for research purposes.

Please fill out the survey based on your previous experience with self-check-in kiosks. If you have little or no experience with check-in kiosks, please fill out the first page and leave the second page blank. Check-in kiosks are an automated system found at airports that allows passengers to independently check-in for their flights. Using the touchscreen interface, travelers can enter booking details, select seats, and print boarding passes without needing assistance from airline staff. The image below shows a typical Self-check-in kiosk.

Illustration of Self-Check in Kiosk (SCK) Systems

Figure 4.3. Cover Page of the Survey

Next, questions regarding the demographic characteristics of participants were asked. The following topics were asked on the second page (Table A.1): gender (nominal), nationality (open-ended), age group (ordinal), background education (nominal), purpose of travel (nominal), frequency of flights (ordinal), ticket class (nominal), and frequency of usage of SCKs (ordinal).

The final section of the survey belongs to the questions that measure the model's variables. It consists of 43 questions for measuring 12 latent variables (Table A.2). Questions for each item were designed in a Likert scale statement format. The Likert scale is a tool for measuring people's attitudes and is used to prepare attitude measurement questionnaires in management and humanities (Sekaran & Bougie, 2016). The survey used a 5-point Likert scale to assess participant agreement with the statements. The 5-point scale expresses agreement with the question, ranging from strongly disagree (1), disagree (2), neutral (3), agree (4), and strongly agree (5).

4.4. Pilot Study

In order to mitigate the risk of using a measurement scale with potential validity and reliability concerns, this research conducted a pilot study. A pilot study is essential to verify the questionnaire's readiness and accuracy for the actual data collection process while also evaluating the consistency of the measurement tool (Pallant, 2013).

The ideal number of participants in the pilot study is accepted by most scholars to be 10 percent of the target sample size (Hertzog, 2008). Whitehead et al. (2016) provided a table that calculated the suggested size for a pilot study based on a standardized effect size with power above 90 percent. The minimum suggested value for the trial sample size was 20. However, other researchers suggested flat numbers as a rule of thumb for the size of a pilot study. For instance, Julious (2005) stated that there should be 12 participants per group in a pilot study. Similarly, Browne (1995) set a general rule for including at least 30 subjects in the pilot study.

For this study, the researcher set the size of the pilot study to be 40 (10% of the target sample size, which was 400). As a result, the designed survey was distributed by hand

and through emails among friends and family members that met the criteria for being included in the sample. Eventually, 40 completed reliable surveys were collected.

Next, a reliability analysis was conducted for the collected data. The general rule of thumb is that the threshold for Cronbach alpha should be values more than 0.7 (Hair et al., 2017). However, according to Pallant (2013), it is difficult to get a value higher than 0.7 for variables with less than 10 items, especially in pilot studies where there are a limited number of participants. She noted that the value of 0.5 allows the researcher to continue with the research. However, variables with less than 0.5 value should be eliminated from the study. Accordingly, The Cronbach's alpha value for each variable and its measuring items were calculated separately and listed in Table 4.2. Based on the above discussion, two variables (facilitating conditions and security) have critically low Cronbach alpha values and must be eliminated from the model. Two variables (functionality and enjoyment) have values less than 0.7 but are greater than 0.5, so they remained in the model until further investigation. As a result, the final model continued with nine latent variables.

Table 4.2. Reliability Analysis of the Pilot Study

Variables	Number of Items	Cronbach's Alpha Value
Effort Expectancy	4	0.852
Performance Expectancy	3	0.868
Social Influence	3	0.940
Facilitating Condition	3	**0.149**
Hedonic Motivation	3	0.919
Functionality	5	**0.573**
Enjoyment	3	**0.628**
Assurance	3	0.851
Security	2	**0.015**
Perceived Risk	3	0.790
Behavioral Intention	3	0.881

4.5. Ethical Consideration

Ethical approval for the dissertation was needed to proceed with the study due to two main reasons. First of all, the designed survey used measuring items from the work of other scholars (Lin & Hsieh, 2011; Venkatesh, Thong, & Xu, 2012). The proof showing the open accessibility of these studies needed to be submitted to Ibn Haldun University Social and Human Sciences Scientific Research and Publication Ethics Committee. Second, the study needed to ask some questions regarding the demographic characteristics of participants. As a result, to ensure that no privacy rules were violated, a copy of the questions was sent to the ethics committee for approval. Eventually, on 08/02/2023, approval and required permission from the ethics committee were granted (Reference number: E-71395021-050.04-36783). The related document is available in Appendix A.

CHAPTER V

DATA ANALYSIS AND RESULTS

Chapter V will illustrate the results obtained from the quantitative analysis of collected data. It starts with discussing the process of data collection and preparing the data for required analysis. Next, it presents the result of a descriptive analysis of participants' demographic and travel characteristics. Then, it discusses the conducted SEM analysis for testing the proposed hypotheses by presenting the reliability, validity, and model fit results. Finally, it investigates the significant levels of path relationships for the proposed model and summarizes the results of the proposed hypotheses.

5.1. Data Collection

The researcher had six visits to target airports (three visits to IGA and three visits to ISG). The date and number of collected data are illustrated in Table 5.1. A total of 404 surveys were collected during these visits.

Table 5.1. Data Collection Process

Airports	Visit Dates	Number of Collected Data
Istanbul Grand International Airport (IGA)	20.08.2023 10.03.2024 12.03.2024	98 74 69
Istanbul Sabiha Gökçen International Airport (ISG)	22.09.2023 23.09.2023 13.03.2024	46 56 61

Some of the kiosks at ISG airport provided the option of self-baggage drop (Figure. 5.1) while the kiosks at IGA only allowed passengers for self-check in process (Figure 5.2).

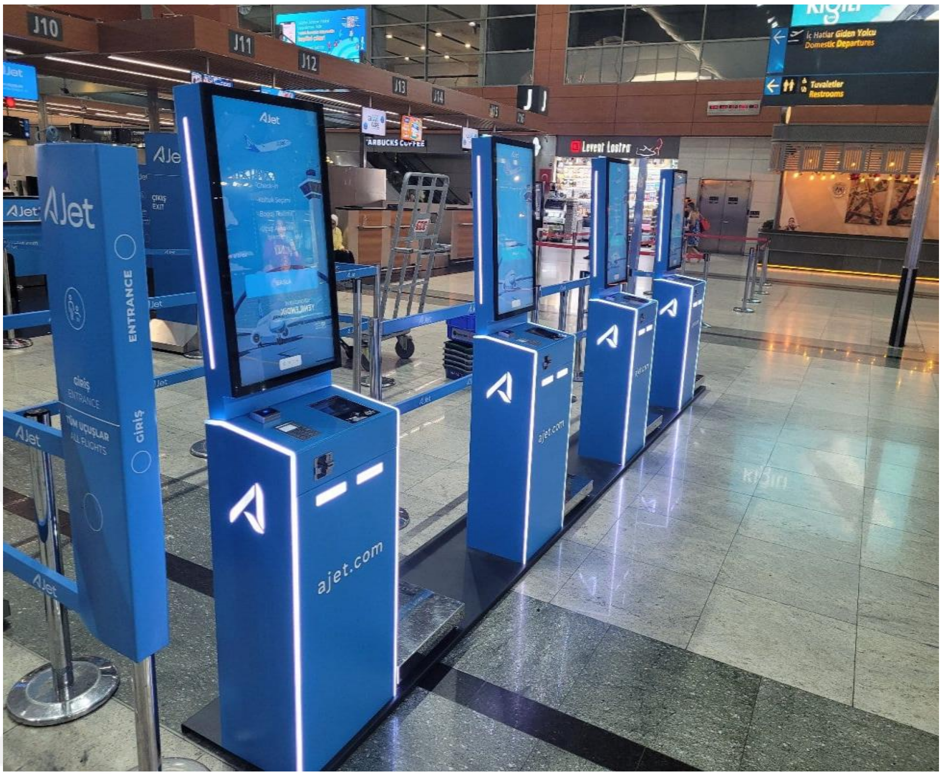

Figure 5.1. SCKs Provided at Istanbul Sabiha Gökçen International Airport

Figure 5.2. SCKs Provided at Istanbul Grand International Airport

After screening the collected surveys, 24 were excluded due to incompleteness. During the data collection process, passengers often needed to take immediate action for their travel journey, which would result in leaving the study unfinished. In addition, some surveys were removed because they showed no signs of participant engagement.

5.2. Data Cleaning

Data cleaning refers to the process of detecting and correcting the missing, corrupt, or incorrect information entered into the data (Hair, 2009). In this study, all data were accurate and properly entered; however, some surveys contained missing values for a few items. As stated in **Table 5.2**, no items have a missing value more than 10%. According to Saunders et al. (2019), the missing response per variable may range from 0.4% to 10%. As a result, there were no extreme missing value problems for the collected data. The item's missing values were replaced by the mean value of the related variable with the SPSS software.

Table 5.2. Missing Value Analysis for Collected Data

Variables	N	Mean	Std. Deviation	Missing		No. of Extremes[a]	
				Count	Percent	Low	High
EE1	380	3.90263	1.031685	0	0.0	0	0
EE2	380	3.8553	0.94860	0	0.0	0	0
EE3	379	3.8338	1.02937	1	0.3	0	0
EE4	377	3.9257	0.93672	3	0.8	28	0
PE1	379	3.9208	1.06858	1	0.3	0	0
PE2	375	3.9760	0.99300	5	1.3	0	0
PE3	379	3.8628	1.03748	1	0.3	0	0
SI1	378	3.3386	0.99954	2	0.5	19	0
SI2	377	3.2865	1.00935	3	0.8	19	0
SI3	379	3.4195	0.96266	1	0.3	19	0
HM1	378	3.6534	0.92648	2	0.5	8	0
HM2	375	3.6267	0.89223	5	1.3	4	0
HM3	377	3.5411	0.96703	3	0.8	13	0

Table 5.2. (cont.)

FU1	378	3.9074	1.01417	2	0.5	0	0
FU2	377	3.6499	0.96174	3	0.8	8	0
FU3	374	3.6123	0.95303	6	1.6	9	0
FU4	380	3.8132	0.96609	0	0.0	0	0
FU5	378	3.1296	1.02831	2	0.5	0	0
EN1	376	3.4814	0.89125	4	1.1	9	0
EN2	378	3.6905	0.95354	2	0.5	11	0
EN3	378	3.3783	0.92548	2	0.5	12	0
ASU1	379	3.3720	0.99009	1	0.3	14	0
ASU2	378	3.4418	0.95692	2	0.5	11	0
ASU3	378	3.3148	0.98737	2	0.5	15	0
PR1	378	2.8069	1.08143	2	0.5	0	0
PR2	378	2.4947	1.06361	2	0.5	0	11
PR3	376	2.7181	1.17316	4	1.1	0	0
BI1	380	3.8237	0.95986	0	0.0	13	0
BI2	380	3.7500	0.98705	0	0.0	16	0
BI3	380	3.8842	0.96769	0	0.0	0	0
a. Number of cases outside the range (Q1 - 1.5*IQR, Q3 + 1.5*IQR).							

5.3. Descriptive Analysis

In this section, the results regarding the demographic characteristics of passengers, including gender, age, education, flight frequency, and flight purposes, are presented.

5.3.1. Demographic Characteristics

A descriptive analysis of the collected for gender, age, and education of participants is illustrated in Table 5.3. The results show that of the 380 participants in the study, 216 were male, and 164 were male, representing 53.8% and 43.2 % of the sample population.

Table 5.3. Descriptive Statistics of Participants for Gender, Age, and Education

	Gender		
	Frequency	Percent	Cumulative Percent
Female	164	43.2	43.2
Male	216	56.8	100.0
	Age		
18 to 24 old	118	31.1	31.1
25 to 34 old	125	32.9	63.9
35 to 44 old	87	22.9	86.8
45 to 54 old	30	7.9	94.7
55 to 64 old	17	4.5	99.2
64 and above	3	0.8	100.0
	Education		
Secondary School Degree	16	4.2	4.2
High School Degree	63	16.6	20.8
Associate degree	38	10.0	30.8
Bachelor’s Degree	169	44.5	75.3
Master’s or Doctorate Degree	94	24.7	100.0

Regarding the age distribution of the sample, the majority of participants (64 %) consisted of individuals between 18 and 35 years old. Individuals aged between 35 and 44 accounted for 22.9 percent of the sample, and the rest of the participants (13 %) belonged to individuals more than 45 years old. The results of participants' educational backgrounds reveal a diverse range of academic qualifications. The majority of respondents had a bachelor’s degree, with 169 individuals (44.5%) indicating it as the most common qualification among the passengers. This is followed by those with a master’s or doctorate degree, totaling 94 individuals (24.7%). The data also shows 63 participants (16.6%) have a high school degree, while 38 individuals (10.0%) hold an associate degree. Finally, only 16 participants (4.2%) had completed a secondary school degree.

5.3.2. Travel Characteristics

According to the sample results, 70% of participants traveled between 0 and 5 times a year. A further 17.4% traveled between 6 and 15 times annually, while 7% traveled between 16 and 25 times yearly. Only 4% of participants traveled more than 26 times yearly (Table 5.4). Regarding travel purposes, 46.8% of participants reported that they travel primarily for personal and leisure reasons, while 20.8% traveled mainly for work and business-related purposes. Additionally, 32.4% of participants indicated that they travel for both personal and business reasons. Finally, only 4.5% of passengers travel most of the time with business seats, and 95.5% travel in economy class.

Table 5.4. Travel Characteristics of Participants

	Fly Frequency		
	Frequency	Percent	Cumulative Percent
0 to 5	270	71.1	71.2
6 to 15	66	17.4	88.7
16 to 25	27	7.1	95.8
Above 26	16	4.2	100.0
	Purpose of Travel		
	Frequency	Percent	Cumulative Percent
Leisure/Personal	178	46.8	46.8
Business/Work	79	20.8	67.6
Both	123	32.4	100.0
	Ticket Type		
	Frequency	Percent	Cumulative Percent
Economy Class	362	95.3	95.5
Business Class	17	4.5	100.0

5.4. Partial Least Square Structural Equation Modeling

As discussed in the previous section, this dissertation employs SmartPLS 4 software to conduct SEM analysis to test and evaluate the proposed model. The collected data was analyzed using the partial least square structural equation modeling (PLS-SEM), a powerful statistical technique for effectively analyzing complex relationships for nonnormal data (Hair et al., 2017). This method is particularly valuable in social and behavioral sciences, where theoretical models often propose complex connections between latent constructs and observed variables. In essence, PLS-SEM consists of two parts: the inner model (measurement model) and the outer model (structural model) (Sarstedt et al., 2021). The following sections will discuss each one in detail.

5.5. Outer Model Assessment

The outer model, also known as the measurement model, focuses on establishing the relationships between latent constructs and their corresponding observed indicators (Hair et al., 2017). It assesses the validity and reliability of measurement instruments by conducting a confirmatory factor analysis (CFA). The CFA will test the constructs' indicator reliability, internal consistency, convergent validity, and discriminant validity (Hair, 2009).

5.5.1. Outer Loadings

First, the outer loading for each observed variable needs to be examined. Basically, the outer loading represents the correlation between observed variables and their corresponding latent variables (Sharma, 1995). In other words, outer loading shows how well the measured variable explains the latent variable it is supposed to represent. Outer loadings of each latent variable should not have a high relationship with other later variables.

Accepted values for outer loadings range between 0.7 and 0.9, and values below 0.7 should be examined with caution (Hair et al., 2017). Consequently, the decision for their removal should be made after looking at internal consistency reliability (Figure 5.3) Items with values less than 0.4 are considered too weak for retaining in the model and should be removed (Hair et al., 2017).

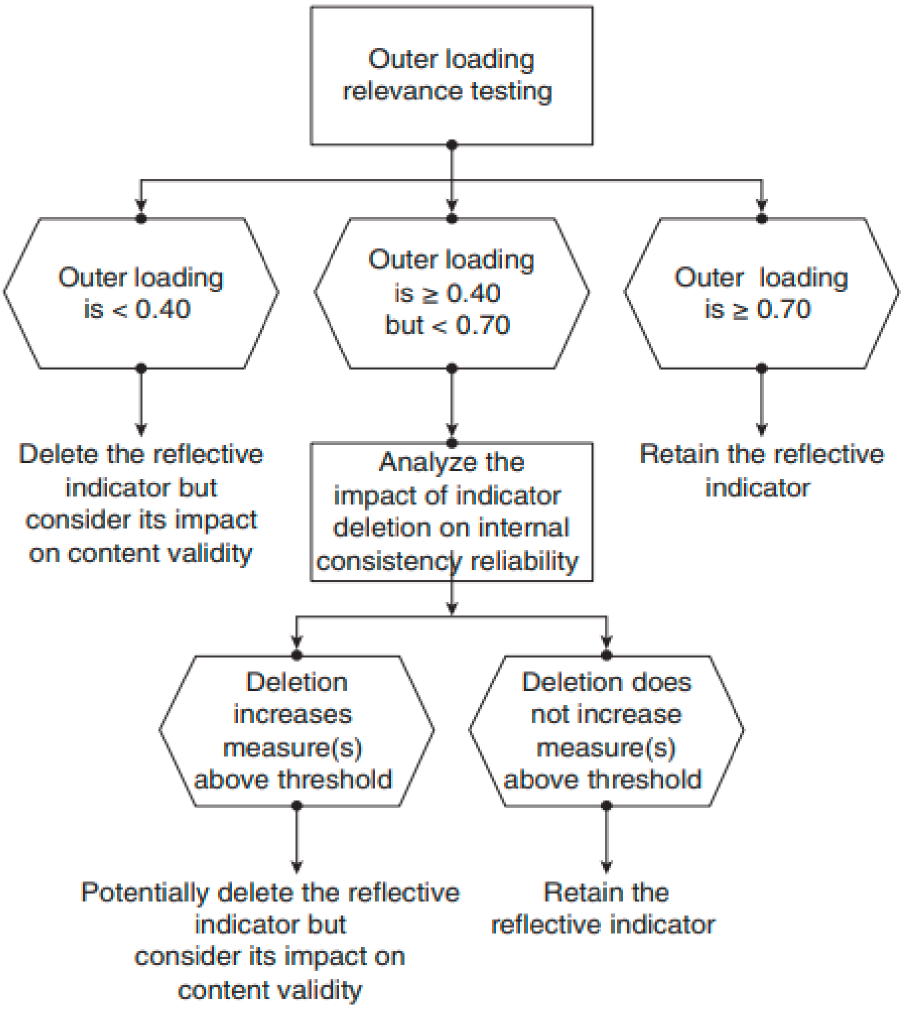

Figure 5.3. Outer Loading Relevance Testing

Source: Hair et al., 2017

The values for all observed variables included in the proposed model are presented in Table 5.5. According to the previous discussion, the only two items that need to be removed are FU5 and PR1 due to their low outer loading values, which are less than 0.5.

Table 5.5. Latent Variable and Outer Loading Values for their Measured Items

	Assurance	Effort Expectancy	Enjoyment	Functionality	Hedonic Motivation	Performance Expectancy	Social Influence	Risk	Behavioral Intention
ASU1	0.894								
ASU2	0.857								
ASU3	0.877								
EE1		0.874							
EE2		0.854							
EE3		0.853							
EE4		0.873							
EN1			0.786						
EN2			0.839						
EN3			0.781						
FU1				0.85					
FU2				0.798					
FU3				0.676					
FU4				0.736					
FU5				0.348					
HM1					0.916				
HM2					0.882				
HM3					0.858				
PE1						0.866			
PE2						0.884			
PE3						0.882			
SI1							0.842		
SI2							0.889		
SI3							0.842		
PR1								0.301	
PR2								0.816	
PR3								0.835	
BI1									0.842
BI2									0.874
BI3									0.873

5.5.2. Construct Reliability and Validity

Construct reliability examines the internal consistency of observed variables with their corresponding latent variables (Sarstedt et al., 2021). To accurately assess the internal consistency reliability of the model, it is recommended to examine both Cronbach's alpha and composite reliability (CR) values (Sekaran & Bougie, 2016). For

Cronbach's alpha, values exceeding 0.7 are considered acceptable, while composite reliability values should ideally fall between 0.7 and 0.9 (Hair et al., 2017). CR values below 0.6 indicate a lack of internal consistency, while values more than 0.95 indicate that the observed variables are too similar to each other and, therefore, they are not likely to be a valid measure of the latent variable.

Convergent validity refers to the degree to which a measurement aligns positively with other measures of the same construct (Sekaran & Bougie, 2016). In other words, the items serving as indicators for a specific reflective construct should exhibit a high level of convergence or share a significant amount of variance (Sarstedt et al., 2021). Outer loading values mentioned in section 5.5.1 and average variance extracted (AVE) are considered as a measure of convergent validity. The suggested value for AVE is 0.5 and higher, which indicates that, on average, the latent variables explain more than 50 percent of the variance in its measuring items. Table 5.6 illustrates an overview value for the construct reliability and validity of variables included in the model. The lowest values recorded for AVE belong to functionality with 0.605, which is higher than 0.5. Similarly, Cronbach's alpha and CR values range between 0.7 and 0.9 for all constructs. Based on the above discussion and obtained results, we can conclude that the model's internal consistency and convergent validity are acceptable.

Table 5.6. Results for Construct Reliability and Validity

Variables	**Internal Consistency Reliability**			**Convergent Validity**
	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average Variance Extracted (AVE)
Assurance	0.849	0.86	0.908	0.768
Social Influence	0.829	0.831	0.897	0.745
Effort Expectancy	0.886	0.887	0.921	0.745
Enjoyment	0.726	0.742	0.844	0.644
Functionality	0.783	0.82	0.859	0.605
Hedonic Motivation	0.862	0.867	0.916	0.784
Performance Expectancy	0.851	0.854	0.909	0.77

Table 5.6. (cont.)

Risk	0.753	0.755	0.858	0.669
Behavioral Intention	0.82	0.823	0.893	0.736

5.5.3. Discriminant Validity

Discriminant validity refers to the extent to which a construct is separated or distinct from other constructs (Hair et al., 2017). In simple terms, it aims to ensure that the measured construct does not overlap with other constructs. The Fornell-Larcker criterion and the heterotrait-monotrait ratio (HTMT) are two popular methods for assessing discriminant validity (Henseler et al., 2015).

Fornell and Larcker (1981) stated that discriminant validity is secured only when the AVE for each construct is greater than the shared variance between that construct and other constructs in the model. As a result, the values on the AVE matrix's main diagonal should be greater than all the values in its corresponding column. Only then can it be stated that the model's discriminant validity is acceptable. Table 5.7 illustrates the Fornell-Larcker results for the study. It is evident that the model passes the Fornell-Larcker Criterion for discriminant validity.

Table 5.7. Discriminant Validity-The Fornell-Larcker Criterion Matrix

	ASU	BI	EE	EN	FUNC	HM	PE	Risk	SI	Use Behavior
Assurance	0.876									
Behavioral Intention	0.347	0.863								
Effort Expectancy	0.279	0.525	0.863							
Enjoyment	0.452	0.511	0.461	0.802						
Functionality	0.415	0.556	0.72	0.552	0.778					
Hedonic Motivation	0.356	0.397	0.481	0.51	0.57	0.885				
Performance Expectancy	0.313	0.572	0.721	0.482	0.662	0.53	0.877			
Risk	0.093	0.035	0.222	0.073	0.136	0.027	0.121	0.818		
Social Influence	0.304	0.399	0.405	0.378	0.406	0.36	0.459	0.02	0.858	
Use Behavior	0.025	0.214	0.335	0.13	0.24	0.137	0.23	0.22	0.141	1

Henseler et al. (2015) developed the heterotrait-monotrait ratio (HTMT) to overcome minor limitations of the Fornell and Larcker method. This ratio is defined as "… the ratio of the between-trait correlations to the within-trait correlations. HTMT is the mean of all correlations of indicators across constructs measuring different constructs (i.e., the heterotrait-heteromethod correlations) relative to the (geometric) mean of the average correlations of indicators measuring the same construct... Technically, the HTMT approach is an estimate of what the true correlation between two constructs would be, if they were perfectly measured (i.e., if they were perfectly reliable)."

The generally accepted threshold for the Heterotrait-Monotrait Ratio is 0.9. If the HTMT value is below 0.90, it indicates that the construct has sufficient discriminant validity (Hair et al., 2017). The HTMT ratio for all constructs in the model is presented in Table 5.8. No values greater than 0.852 (Functionality <-> Effort Expectancy) were recorded. Based on the obtained result for the Fornell-Larcker and HTMT ratio, it can be concluded that the discriminant validity for the model is secured.

Table 5.8. Discriminant Validity-Heterotrait-Monotrait Ratio (Listwise)

Correlation Path	Heterotrait-monotrait ratio (HTMT)
Behavioral Intention <-> Assurance	0.41
Effort Expectancy <-> Assurance	0.32
Effort Expectancy <-> Behavioral Intention	0.611
Enjoyment <-> Assurance	0.57
Enjoyment <-> Behavioral Intention	0.649
Enjoyment <-> Effort Expectancy	0.567
Functionality <-> Assurance	0.511
Functionality <-> Behavioral Intention	0.67
Functionality <-> Effort Expectancy	0.852
Functionality <-> Enjoyment	0.706
Hedonic Motivation <-> Assurance	0.411
Hedonic Motivation <-> Behavioral Intention	0.468
Hedonic Motivation <-> Effort Expectancy	0.548

Table 5.8. (cont.)

Hedonic Motivation <-> Enjoyment	0.632
Hedonic Motivation <-> Functionality	0.68
Performance Expectancy <-> Assurance	0.362
Performance Expectancy <-> Behavioral Intention	0.679
Performance Expectancy <-> Effort Expectancy	0.83
Performance Expectancy <-> Enjoyment	0.599
Performance Expectancy <-> Functionality	0.796
Performance Expectancy <-> Hedonic Motivation	0.622
Risk <-> Assurance	0.129
Risk <-> Behavioral Intention	0.051
Risk <-> Effort Expectancy	0.271
Risk <-> Enjoyment	0.122
Risk <-> Functionality	0.181
Risk <-> Hedonic Motivation	0.066
Risk <-> Performance Expectancy	0.151
Social Influence <-> Assurance	0.366
Social Influence <-> Behavioral Intention	0.485
Social Influence <-> Effort Expectancy	0.471
Social Influence <-> Enjoyment	0.481
Social Influence <-> Functionality	0.499
Social Influence <-> Hedonic Motivation	0.43
Social Influence <-> Performance Expectancy	0.55
Social Influence <-> Risk	0.084
Use Behaviour <-> Assurance	0.049
Use Behaviour <-> Behavioral Intention	0.234
Use Behaviour <-> Effort Expectancy	0.354
Use Behaviour <-> Enjoyment	0.148
Use Behaviour <-> Functionality	0.256
Use Behaviour <-> Hedonic Motivation	0.146

Table 5.8. (cont.)

Use Behaviour <-> Performance Expectancy	0.251
Use Behaviour <-> Risk	0.247
Use Behaviour <-> Social Influence	0.158

5.5.4. Common Method Bias Test

Common method bias refers to a systematic error that occurs when data for multiple variables are collected using the same method, often from the same respondents (Sarstedt et al., 2021). According to Kock (2015), a common method bias problem can be detected using the SmartPLS software by looking at variance inflation factor (VIF) values for included constructs in the model. In general, VIF is used to detect multicollinearity problems in regression analysis. Multicollinearity occurs when a high correlation exists between two or more independent variables in the model (Schumacker & Lomax, 2004).

If the obtained VIF values in the model are greater than 3.3, then there is a possibility that the model is contaminated with common method bias. In contrast, if all values for VIF in the inner model are less than 3.3, it is safe to state that the model is free of common method bias (Kock, 2015). Table 5.9 illustrates the VIF values for the model. The highest value was 2.746, which is below the threshold value. Based on the above discussion and the results obtained for the VIF values of the model, it can be concluded that the model is free from common method bias.

Table 5.9. Collinearity Statistics (VIF)

Relationships	VIF
Assurance -> Behavioral Intention	1.358
Behavioral Intention -> Use Behavior	1.027
Effort Expectancy -> Behavioral Intention	2.691
Enjoyment -> Behavioral Intention	1.728
Functionality -> Behavioral Intention	2.746
Hedonic Motivation -> Behavioral Intention	1.703

Table 5.9. (cont.)

Performance Expectancy -> Behavioral Intention	2.506
Risk -> Use Behavior	1.04
Social Influence -> Behavioral Intention	1.359
Risk x Behavioral Intention -> Use Behavior	1.068

5.5.5. Model Fit

Model fit refers to measuring the compatibility of a theoretical model with an experimental model. In other words, it measures the degree of correspondence between the hypothesized model and the observed data (Schumacker & Lomax, 2004). Several indicators are introduced to check the goodness of fit for models, and each one has its own acceptable range (Jöreskog & Sörbom, 2006). For this study, the model fit was tested through covariance-based structural equation modeling (CM-SEM).

The most popular model fit indices are root mean square error of approximation (RMSEA) developed by Steiger (1990) with the acceptable range of 0.05 to 0.1, normal-fit index (NFI) developed by Bentler and Bonett (1980) with the threshold value of NFI>0.8, comparative fir index (CFI) developed by Bentler (1990) with a cut-off criterion of CFI ≥ 0.90, goodness-of-fit statistic (GFI) and adjusted goodness-of-fit statistic (AGFI) developed by Jöreskog and Sörbom (2006) with suggested value of greater than 0.9, and standardized root mean square residual (SRMR) with suggested value of less than 0.5 (Jöreskog & Sörbom, 2006).

The values for the discussed indices for the proposed model are illustrated in Table 5.10. The obtained results prove that the model fits the data with absolute fit scores of RMSEA 0.052, NFI 0.904, CFI 0.954, GFI 0.906, AGFI 0.875, and SRMR 0.039.

Table 5.10. Model Fit Indices

The goodness of fit indices	Recommended values	Model values
RMSEA	<0.10	0.052
NFI	>0.90	0.904
CFI	>0.90	0.954
GFI	>0.90	0.906
AGFI	>0.80	0.875
SRMR	<0.10	0.039

5.6. Inner Model Assessment

The inner model, also known as the structural model, investigates the hypothesized relationships among the latent constructs and their observed variables. It tests the proposed causal connections between constructs and evaluates the overall fit of the theoretical model to the observed data. For this study, the PLS-SEM was conducted to test the inner model with 5000 subsample bootstrapping. The test type was a two-tailed test with a 0.05 significant level.

The graphical output of the model with outer loading/weights for measured items and the path coefficient of the relationships are illustrated in Figure 5.4.

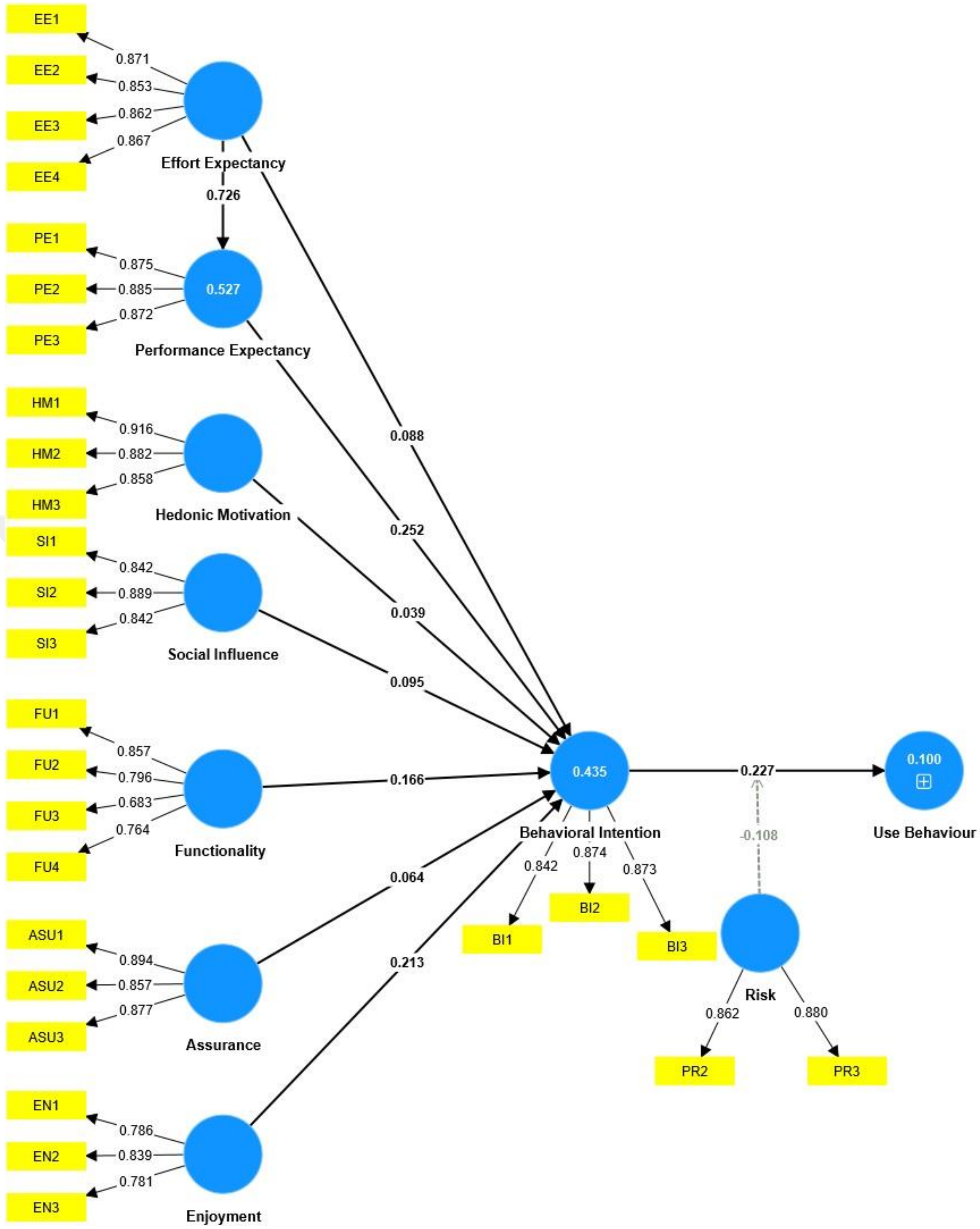

Figure 5.4. SEM Path Model

5.6.1. R-square and Adjusted R-square

In simple words, the R-square shows the explanatory power of the model (Kline, 2023). It illustrates how much of the variance in the endogenous variable (dependent variable) is explained by the exogenous variables (independent variables) (Schumacker & Lomax, 2004). The value of this index is between zero and one, and if the value of R^2 exceeds 0.6, it indicates that the exogenous variables account for a significant proportion of the variability in the endogenous variable.

The values for the R square and adjusted R square of the model are illustrated in Table 5.11. In addition, the values UTAUT and UTAUT 2 models were added to the table for comparison. The obtained values for R^2 and adjusted R^2 of behavioral intention (dependent variable) in the proposed model are 0.436 and 0.422, respectively. These values indicate that almost 44% of the variance in the behavioral intention of passengers for using self-check-in kiosks is explained by the included independent variables in the model. Compared to the original UTAUT and UTAUT 2 models, which accounted for R^2 values of 0.35 and 0.44, the obtained result for the model is considered acceptable. A similar statement can be made for the endogenous variable use behavior. The R^2 and adjusted R^2 values for use behavior in the model is close to the original models and considered acceptable.

Table 5.11. Comparison of R2 Values of Model with UTAUT Models

Dependent Variable		UTAUT	UTAUT 2	Proposed Model
Behavioral Intention	R^2	0.35	0.44	0.436
Use Behavior	R^2	0.26	0.35	0.22

5.6.2. Path Analysis

Path analysis is a statistical technique rooted in multivariate regression that examines the relationships between variables within a model (Barclay et al., 1995). It utilizes standardized regression coefficients to assess both the direction and strength of the relationships between variables using the t-statistic which indicates the significance of relationships (Hair et al., 2017). Values that show the direction and intensity of paths are called path coefficients, and it is shown universally with the symbol β. The path coefficient indicates the strength of the relationship between two latent variables. The path coefficients can be significant at the confidence level of 0.1 (t-value greater than 1.645), 0.05 (t-value greater than 1.96), and 0.01 (t-value greater than 2.576) (Sekaran & Bougie, 2016). The path analysis results for the model are illustrated in Table 5.12.

Table 5.12. Path Analysis of the Model

Path Coefficients	Original sample β	Sample mean	Standard deviation	T statistics	P values
Assurance -> Behavioral Intention	0.064	0.062	0.051	1.246	0.213
Behavioral Intention -> Use Behavior	0.227	0.232	0.058	3.893	0***
Effort Expectancy -> Behavioral Intention	0.088	0.085	0.083	1.051	0.293
Effort Expectancy -> Performance Expectancy	0.726	0.727	0.028	25.92	0***
Enjoyment -> Behavioral Intention	0.213	0.214	0.07	3.025	0***
Functionality -> Behavioral Intention	0.166	0.167	0.084	1.968	0.049**
Hedonic Motivation -> Behavioral Intention	0.039	0.034	0.078	0.507	0.612
Performance Expectancy -> Behavioral Intention	0.252	0.249	0.074	3.426	0***
Risk -> Use Behavior	0.219	0.225	0.056	3.933	0***
Social Influence -> Behavioral Intention	0.095	0.099	0.052	1.82	0.069*
Risk x Behavioral Intention -> Use Behavior	-0.108	-0.112	0.064	1.682	0.093*

****p<0.01, **p<0.05, *p<0.10*

The path analysis results indicate that assurance, effort expectancy, and hedonic motivation do not significantly influence behavioral intention. In contrast, enjoyment, functionality, performance expectancy, and social influence are significant predictors of behavioral intention. Performance expectancy (*p*-value=0, t=3.426) exerts the strongest influence (0.01 confidence level), followed by enjoyment (*p*-value=0, t=3.025) and functionality (*p*-value = 0.049, t=1.968) with 0.05 confidence level, while social influence (*p*-value=0.069, t=1.82) has the weakest significant impact (0.1 confidence level) on behavioral intention. In addition, the effect of effort expectancy on performance expectancy is significant (*p*-value=0, t=25.92) at a 0.01 significant.

5.6.3. Moderating Effect of Perceived Risk

The proposed model assessed the moderating role of perceived risk (PR) on the relationship between behavioral intention (BI) and use behavior (UB). As illustrated in Table 5.12, the results of path analysis between BI and UB indicate that the moderating effect of risk on the relationship is significant at 0.1 level of confidence (*p*-value=0.093, t=1.682). This result shows that the relationship between BI and UB will be weakened with an increase in perceived risk.

In addition, in order to better illustrate the nature of the moderation effect of risk, a slop analysis is presented in Figure 5.5. As shown in the figure below, the line is much steeper when the value for risk is low (blue line). This means that at the low level of perceived risk, the impact of BI on UB is much stronger in comparison when the value for risk is high (red line). However, at a higher level of risk, the line tends to straighten, which means that at a higher level of perceived risk, the increase in BI does not lead to a similar variance in UB. In short, a higher level of perceived risk dampens/weakens the impact of BI on UB.

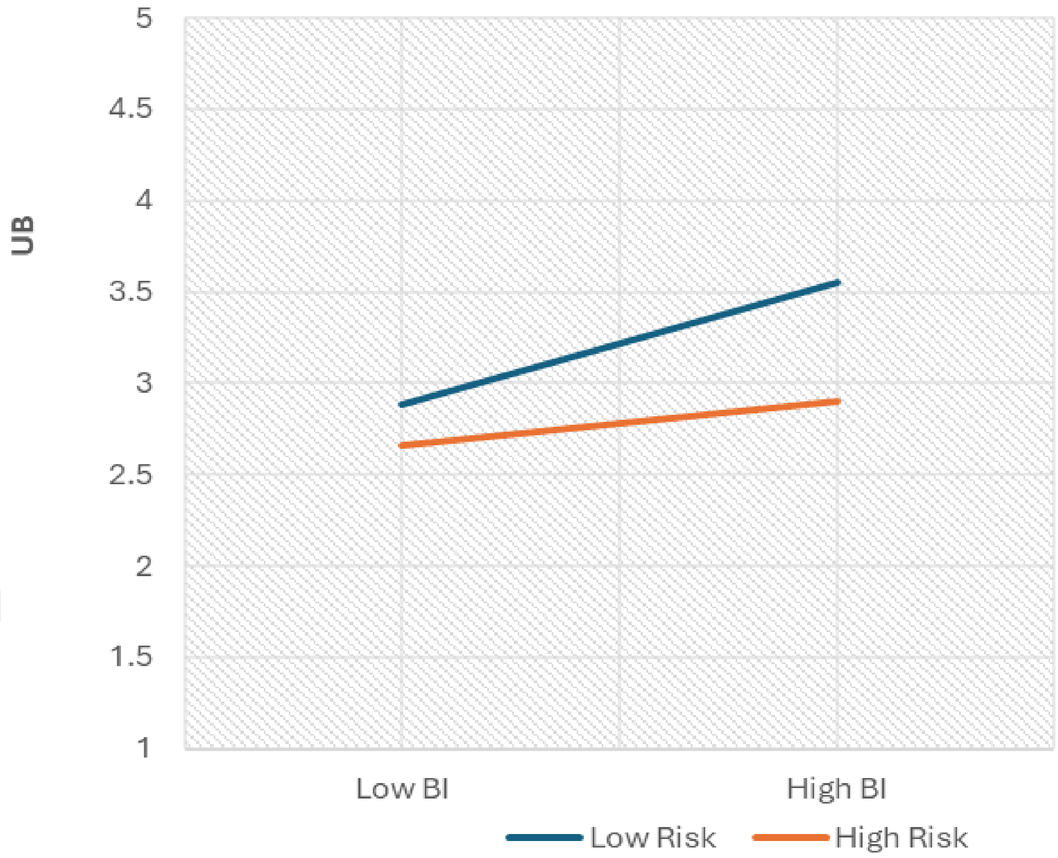

Figure 5.5. The Slop Analysis of Moderator Effect of Risk on BI->UB

Furthermore, the F-square effect size for the moderator effect of risk was calculated as 0.015. According to Kenny (2018), values of F^2 for 0.005, 001, and 0.025 are considered small, medium, and large sizes of moderation, respectively. As a result, it can be stated that perceived risk has a medium moderating effect on the relationship between BI and UB.

5.7. Hypotheses Testing

Based on the results obtained and the previous discussion, the table was developed to summarize the proposed hypotheses and their corresponding outcomes (Table 5.13.)

Table 5.13. Results of Proposed Hypotheses

Hypotheses	Expected sign	Path Coefficient (β) and sig lvl	Results
H_1: Performance Expectancy of passengers regarding SCKs will have a positive direct effect on BI	+	0.252***	Accepted
H2: *Effort Expectancy of passengers regarding SCKs will have a positive direct effect on BI.*	+	0.088	Rejected
H_3: *Effort Expectancy will have a positive direct effect on the performance expectancy of passengers.*	+	0.726***	Accepted
H_4: *Hedonic Motivation will have a positive direct effect on the BI of passengers toward SCKs.*	+	0.039	Rejected
H_5: *Social Influence will have a positive direct effect on the BI of passengers toward SCKs.*	+	0.095*	Accepted
H_6: *Facilitating Condition will have a positive direct effect on the BI of passengers toward SCKs.*	+	Removed	Removed
H_7: *Functionality will have a positive direct effect on the BI of passengers toward SCKs.*	+	0.166**	Accepted
H_8: *Assurance will have a positive direct effect on the BI of passengers toward SCKs.*	+	0.064	Rejected
H_9: Security will have a positive direct effect on the behavioral intention of passengers toward SCKs.	+	Removed	Removed
H_{10}: *Enjoyment will have a positive direct effect on the BI of passengers toward SCKs.*	+	0.213***	Accepted
H_{11}: Perceived risk will have a moderating effect on the relationship between BI and behavioral usage of passengers toward SCKs.	-	-0.108*	Accepted

CHAPTER VI

CONCLUSION AND DISCUSSION

The journey of this dissertation began with conducting a scoping review for the application of artificial intelligence (AI) in airports. The study's results highlighted a critical gap: ignoring the passengers' perspectives. Interestingly, the least explored but arguably most critical topic is the examination of passengers' perspectives and attitudes toward the use of such technologies (Haji Amiri & Kusakci, 2024). Consequently, the researcher focused on identifying key touchpoints where passengers may directly interact with AI-based technologies. One such topic was identified to be interactive kiosks. However, the adoption of kiosks by passengers is still evolving, and there appears to be a considerable journey ahead before reaching full maturity (H. L. Chang & Yang, 2008; Obermeier et al., 2022). In addition, cultural and distinct regional characteristics may further influence the pace and trajectory of this process (Ku & Chen, 2013). As a result, the first goal should be to identify factors that affect passengers' behavior intentions toward kiosks.

Modern airports are undergoing a digital transformation characterized by a shift towards passenger self-service to empower passengers and increase their flexibility in times of crisis (Serrano & Kazda, 2020). Self-service technologies (SSTs) are at the forefront of this evolution, encompassing a range of innovations (Djelassi et al., 2018). Integration of such technologies in airport operations has various benefits for all stakeholders. Research has demonstrated that these technologies can contribute to cost reduction (Shady G. Abdelaziz, 2010), enhanced performance (Antwi et al., 2021), improved passenger travel experience (Kim et al., 2019), increased satisfaction (Bogicevic et al., 2017) and loyalty (Kilic, 2019). One of the most commonly known types of SSTs is interactive kiosks (Vakulenko et al., 2018).

Interactive kiosks can be utilized as airport infrastructure designed to help passengers check-in quicker and easier (Drennen, 2011), which can eventually result in reducing airport and airline costs (Djelassi et al., 2018). As a result, airport administration and aviation authorities should prioritize increasing the number of passengers who adopt these technologies by understanding the significant factors that develop passenger behavior.

A review of the literature on interactive airport kiosks identifies several critical issues. While studies examining airport kiosks are limited, research specifically focused on self-check-in kiosks (SCKs) is exceedingly scarce, with fewer than five studies identified (Geantoro, 2020; Samy, 2017; Singh, 2018). Most previous works exploring airport kiosks considered them as part of a broader category of self-service technologies (Antwi et al., 2021). However, Vakulenko and his colleagues argue that, for comprehensive understanding, kiosks demand their own distinct conceptual framework (Vakulenko et al., 2018, 2019).

Another issue is that the majority of previous studies have concentrated on the marketing implications of airport kiosks, primarily examining their influence on passenger satisfaction (Antwi et al., 2021; J. H. Kim & Park, 2019; Wittmer, 2011), brand loyalty (Kilic, 2019), and perceived value (Kim et al., 2019). A limited body of research has examined passenger behavioral intentions and usage patterns concerning airport SSTs (Kusumah et al., 2021; Lu et al., 2009; Untaru et al., 2024). Among studies that have investigated passenger behavioral intentions toward airport kiosks, the majority of these studies have relied exclusively on the Technology Acceptance Model (TAM) as a theoretical framework (Kim et al., 2019; Ku & Chen, 2013; Lu et al., 2009; Taufik & Hanafiah, 2019). While TAM is a valid and reliable framework, its primary focus on organizational users (i.e., employees or managers) limits its applicability to understanding customer behavior (Malatji et al., 2020; Momani et al., 2017). Comparatively, only a handful of studies (Geantoro, 2020; Samy, 2017) have employed the Unified Theory of Acceptance and Use of Technology (UTAUT) or UTAUT2, which are considered to be much newer robust models that have customer-centric perspectives (S.-M. Lee et al., 2018; Samy, 2017; Zamorano et al., 2020). Furthermore, recent research has advocated integrating quality assessment measures into existing technology acceptance models (Malanga et al., 2022).

Finally, a geographical bias is evident in the existing body of research on airport kiosks. While studies acknowledge the influence of regional factors on passenger kiosk adoption, the empirical evidence is concentrated primarily on Western European contexts (Lu et al., 2009). Although some research has explored Asian markets (Ghosh, 2021), the Middle East remains significantly underrepresented.

In order to address all the mentioned issues, this dissertation proposed a model that combined two established models: UTAUT2 and the Self-Service Technology Service Quality (SSTQUAL) scale developed by Lin & Hsieh (2011). The research aimed to explore determinant factors affecting passengers' behavioral intention toward self-check-in kiosks at two major airports in Türkiye, Istanbul Grand Airport (IGA) and Istanbul Sabiha Gökçen (ISG) Airport. The backbone of the proposed model was composed of the UTAUT 2 model and included the following dimensions: effort expectancy (EF), performance expectancy (PE), hedonic motivation (HM), social influence (SI), facilitating condition (FC), behavioral intention (BI), use behavior (UB) with having the last two dimensions as endogenous variables and rest as exogenous variables. The rest of the dimensions included in the model came from the SSTQUAL model. They are as follows: functionality (FU), assurance (ASU), enjoyment (ENJ), and security (SEC). Moreover, the moderating effect of perceived risk (PR) on the relationship between BI and UB was investigated. Structural Equation Modeling (SEM) was utilized to test the proposed model and its hypotheses. Three hundred eighty completed and valid surveys were collected from both airports by hand. IBM SPSS and SmartPLS 4 software were used to analyze the collected data.

This dissertation proposed eleven hypotheses, examining the positive influence of exogenous variables (EE, PE, HM, SI, FC, FU, ASU, ENJ, and SEC) on behavioral intention (BI), as well as the negative moderating effect of perceived risk on the relationship between BI and usage behavior. In addition, the positive effect of effort expectancy on performance expectancy was also proposed. Of the eleven hypotheses proposed, six were supported (H_1, H_3, H_5, H_7, H_{10}, H_{11}), three were rejected (H_2, H_4, H_8), and two were eliminated (H_6, H_9) due to lack of reliability in constructs. Due to the exclusion of security and facilitating conditions from the model, no statement regarding their impact on behavioral intention can be drawn.

The findings of the study indicate that performance expectancy (H_1) is the strongest factor (β= 0.252). This result aligns with a similar previous study conducted by Geantoro (2020). This indicates that passengers are more likely to check in with kiosks if they feel using the kiosks is useful and will help them go through the check-in process much quicker and faster. Previous research employing the TAM models has consistently demonstrated a positive relationship between perceived usefulness (a construct parallel to performance expectancy, with comparable measurement items) and BI of passengers toward kiosks (Lu et al., 2009) and other types of SSTs in airports (Taufik & Hanafiah, 2019). In addition, similar statements can be made for performance expectancy in other industries. For instance, effort expectancy has been shown to have a significant effect on BI for electronic banking services and online payment (Ghalandari, 2012; Rahi et al., 2019), mobile learning in education (Sung et al., 2015), online food delivery (Tannady & Dewi, 2024), and mobile health care services (Utomo et al., 2021).

Similar statements can be made for the functionality variable and its effect on the behavioral intention of passengers toward SCKs (H_7). Functionality exhibited a positive and significant influence on behavioral intention (β = 0.166), although this effect was less powerful than that of performance expectancy. These findings align with Venkatesh and Davis (2000), who emphasized the critical role of ease of use and clarity in fostering technology acceptance. Furthermore, the results support the findings of research by Parasuraman and Grewal (2000), who highlighted that a clear service process and minimal effort are essential factors in service quality perceptions and user satisfaction. In the context of airports, Kim and Park (2019b) found that the characteristics of SSTs, such as functionality, enjoyment, customization, and convenience, play a crucial role in shaping behavioral intentions. In the study, they found that the effect of functionality on BI is mediated through perceived values and customer satisfaction. In other words, when the functionality of the self-service technologies meets or exceeds passenger expectations, it positively impacts their intention to continue using these services. Interestingly, a previous study found that functionality did not significantly influence behavioral intention toward self-service kiosks equipped with biometric authentication (Obermeier et al., 2022).

Enjoyment was the second strongest factor influencing passengers' BI toward kiosks (β= 0.252). The findings from this study underscore a crucial element in enhancing passengers' engagement with self-check-in kiosks (SCKs). Generally speaking, when SST users experience a sense of accomplishment and satisfaction from independently managing their services, it enhances their overall perception of the service and encourages frequent use (Ghosh, 2021). Venkateswaran (2020) also came to a similar conclusion using SSTQUAL for Indian Metropolitan City Airports. A closer examination of measuring items for the enjoyment variable reveals that when passengers find the technology fascinating and stimulating, they are more encouraged to adopt SCKs as a preferred check-in method. In addition, one of the items (EN3: checking in with SCKs has interesting additional functions and features) highlights the importance of exclusive benefits in user experience. Features that extend beyond basic check-in capabilities, such as personalized options or interactive interfaces, can significantly heighten user interest and engagement. A similar suggestion was made in one of the early studies regarding the use of kiosks in airports by Chang & Yang (2008), in which they encouraged airlines to mitigate frequent flyer reluctance to use kiosks by offering supplementary rewards or seat-selecting privileges.

Another significant, yet less powerful (β= 0.095), factor was the social influence. The findings show that SI positively and significantly impacts passengers' behavioral intention to utilize SCKs. This result is consistent with very similar (β= 0.098) findings of Geantoro (2020), who used the UTAUT 2 model for evaluating the BI of passengers toward SCKs at Jakarta Metropolitan Airport in Indonesia (Geantoro, 2020). This result aligns with the broader literature on consumer behavior, which underscores the role of social factors in shaping individuals' attitudes and intentions (Malhotra & Galletta, 1999; Ryan, 1982).

The obtained result suggests that airlines should leverage social networks and word-of-mouth to encourage passengers to adopt SCKs, especially when taking into account the power of social media in shaping consumer behavior. By leveraging social media, airlines and airports can work together to effectively spread information about the benefits of SCKs, generate positive word-of-mouth, and create a sense of social desirability associated with using these technologies. In addition, content created by social media influencers or ordinary passenger reviews can be particularly influential in shaping perceptions and encouraging the adoption of SCKs.

This study also investigated the effect of effort expectancy on performance expectancy (H_3). The results indicate that there exists a strong and positive relationship between the two variables (β= 0.726). Similar strong effects were reported in multiple studies in the past (Do Nam Hung et al., 2019; J. H. Kim et al., 2023; Rahi et al., 2019; Sung et al., 2015). This robust relationship suggests a compelling interplay between perceived exertion and anticipated outcomes. Passengers are more likely to believe they can successfully check in to their flight through SCKs if they view the check-in process as straightforward and user-friendly. Conversely, if the process seems complex or difficult to navigate, they may feel discouraged and doubt their ability to complete the check-in effectively. This strong relationship underscores the importance of designing kiosks that minimize perceived effort while maximizing the perceived value of the outcome.

The result of the study also rejected the significant effect of effort expectancy (H_2) on the BI of passengers. This unanticipated result states that passengers' willingness to use self-check-in kiosks is not heavily influenced by how easy or challenging they perceive the technology. In other words, it suggests that factors other than perceived ease of use play a more critical role in shaping passengers' intentions. Factors such as having an error-free experience or the speed of the check-in process might overshadow concerns about the effort required to interact with the kiosk.

Although there are few studies that support this result, the majority of literature supports that effort expectancy is a significant factor for BI. One of the few studies that supports the result of this study was conducted by Jeon et al. (2019), who found that effort expectancy does not significantly affect the intention of passengers to use smartphone apps for booking and purchasing flight tickers (Jeon et al., 2019). Korkmaz et al. (2022) also found that hedonic motivation does not significantly contribute to the BI of users for autonomous public transport. Besides the mentioned studies, the rest of the literature found the opposite result to the obtained results in this study. For instance, Geantoro (2020) found a significant and relatively strong relationship (β= 0.276) between effort expectancy and BI of passengers for using

SCKs in Soekarno–Hatta International Airport. Similarly, Samy (2017) stated that effort expectancy has the strongest effect on the behavioral intention of passengers for using SSTs among all factors. In addition, studies in other industries, such as the food service industry for online ordering and delivery (Tannady & Dewi, 2024), education for mobile learning, healthcare (Utomo et al., 2021), and baking for mobile payment (Do Nam Hung et al., 2019) proved a significant and positive relationship between EE and BI.

One possible explanation for this contradiction in the obtained result and previous studies could be that passengers are already familiar with kiosks or accustomed to similar technologies (ATMs, grocery store kiosks, hotel self-check-in kiosks, etc.) in other industries, reducing the impact of effort expectancy on their decision-making process. Moreover, the lack of a significant effect could also reflect the design and usability improvements that have been made to self-check-in kiosks recently. All previously mentioned studies were conducted at least five years prior to this research. As these kiosks become increasingly user-friendly, the effort expectancy might be perceived as minimal across the board, thus rendering it less influential on behavioral intention.

For instance, the convenience and speed of the check-in process might overshadow concerns about the effort required to interact with the kiosk. Additionally, it is possible that passengers are already familiar with or accustomed to similar technologies, reducing the impact of effort expectancy on their decision-making process. Moreover, the lack of a significant effect could also reflect the design and usability improvements that have been made to self-check-in kiosks over time. As these kiosks become increasingly user-friendly, the effort expectancy might be perceived as minimal across the board, thus rendering it less influential on behavioral intention.

Another rejected hypothesis was related to the positive effect of hedonic motivation on behavioral intention (H_4). There are similar results in the literature that align with these findings. Hanantyo and Mahmudi (2024) used the UTATU 2 model in Indonesian airports to investigate the factors that affect the behavioral intention of passengers for using SSTs. They found that all the variables except hedonic motivation have a significant effect on the behavioral intention of passengers (Hanantyo &

Mahmudi, 2024). A similar result was confirmed by Korkmaz et al. (2022), who investigated factors affecting users' acceptance and use of autonomous public transport systems and found that hedonic motivation is not a significant factor in users' behavior intention (Korkmaz et al., 2022).

This result suggests that passengers do not prefer to include entertainment aspects in the SCKs. Although this outcome may contrast with the expectations of many in the travel industry, who often prioritize entertainment and enjoyment, these results reflect the seriousness of travel journeys that most passengers experience in airports. Air travel can be stressful for many individuals for many reasons, such as time pressure, security concerns, and potential language barriers. It is possible that the hedonic aspects of using SCKs, while positive, are not sufficiently compelling to outweigh other factors that influence behavioral intention. In other words, passengers may prioritize efficiency and reliability over enjoyment when choosing between traditional check-in counters and self-check-in kiosks. It is important to note that the variable "enjoyment," which emerged as significant in this study (H_{10}), did not encompass items related to entertainment. Instead, it focused on evaluating the interesting features and functions of SCKs and the overall user experience and satisfaction that passengers experience during use. This distinction highlights that the enjoyment derived from using SCKs is more closely associated with engaging features and positive interactions rather than merely entertainment value.

The last rejected hypothesis was related to variable assurance (H8). Unfortunately, limited commentary can be offered on this result due to the lack of prior research investigating how airport, city, and country reputations can influence passengers' behavioral intentions. This outcome suggests that the broader reputational context, such as the airport's image in passengers' minds, the city's infrastructure, or the country's technological advancement, does not play a crucial role in shaping passengers' willingness to adopt SCKs. Instead, passengers may prioritize the characteristics of SCKs and their direct practical aspects, such as perceived performance. Another explanation for the obtained result is that many passengers may anticipate consistent experiences across different locations when using SCKs, potentially perceiving them as standardized devices such as ATMs.

Finally, the results of the study prove that perceived risk has a negative moderating effect on the relationship between passengers' behavioral intention and actual use of SCKs (H_{11}). The negative moderating effect of perceived risk suggests that even if passengers express a strong intention to use SCKs, their actual usage may be hindered by anxieties related to the potential risks, such as the possible irreversible mistakes, nervousness, and the fear of missing a flight due to errors while using SCKs. This result was anticipated, and the literature also supports it.

To our knowledge, this study is the first to investigate the moderating effect of perceived risk on behavioral intention toward SCKs. However, previous research consistently highlighted a significant negative relationship between perceived risk and the intention to adopt new technologies. Lee and Song (2013) used the UTAUT2 model to indicate the negative significance of perceived risk on the intention to use new technology among their sample participants. Kaur and Arora (2020) found that perceived risk as a multi-dimensional construct has a direct and indirect impact on BI via performance expectancy, social influence, and hedonic motivation. Rifat et al. (2019) defined second-order variables for perceived risk by including performance risk, individual risk, financial risk, time risk, and cyber risk. They added perceived risk into the TAM model and examined the effect of perceived risk on BI, perceived usefulness, and perceived ease of use. It was found that perceived risk has a significant negative effect on the user's BI. Moreover, they showed that perceived risk is inversely related to perceived usefulness.

This moderating effect underscores the importance of addressing perceived risks to enhance the adoption of self-check-in kiosks. By alleviating these concerns through user-friendly designs, clear instructions, and continuous maintenance, airports and airlines can help reduce the negative impact of perceived risk on the actual use of SCKs. Consequently, improving passengers' confidence in using these kiosks can bridge the gap between their behavioral intentions and actual usage, fostering a more seamless and widespread adoption of self-service technologies.

6.1. Limitation of the Study

This study is subject to several limitations. Firstly, while the UTAUT2 and SSTQUAL models provide a robust framework for understanding SCK adoption, the exclusion of certain variables (security and facilitating conditions) might have limited the model's explanatory power. Future research should attempt to include more measuring items in order to explore the effect of mentioned variables under different conditions.

Second, the geographical scope is restricted to two major airports in Istanbul, Türkiye. Consequently, the generalizability of the findings to other airport contexts with varying passenger demographics, infrastructure, and technological advancements might be constrained. Next, the research exclusively focused on the passenger perspective, overlooking the viewpoints of other crucial airport stakeholders. A broader perspective incorporating the opinions of airline personnel, airport management, and security staff could provide a more comprehensive understanding of SCK adoption.

Additionally, the cross-sectional research design limits the ability to examine changes in passenger behavior over time, hindering the identification of dynamic patterns in SCK usage. Finally, the reliance on self-reported data through surveys and the presence of researcher during the survey could introduce the potential for social desirability bias, which might overestimate positive attitudes and behaviors toward SCKs.

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APPENDIXES

APPENDIX A

Table A.1. Survey Question: Demographic Questions

1) My gender is:

Female ☐
Male ☐

2) My nationality/home country is ……………………………

3) My age is:

18 to 24 years old ☐ 45 to 54 years old ☐
25 to 34 years old ☐ 55 to 64 years old ☐
35 to 44 years old ☐ 65 and above ☐

4) My education level is:

Secondary School Degree ☐ Bachelor's Degree ☐
High School Degree ☐ Master's or Doctorate Degree ☐
Associate degree ☐

5) The purpose of most of my travels is:

Leisure/Personal ☐
Business/Work ☐
Both ☐

6) Annually, I fly the following number of times:

0-5 ☐ 16 to 25 ☐
6 to 15 ☐ 26 and above ☐

7) Mostly, I travel with:

Economy Class ☐ Business Class ☐

8) The airline that I usually fly with is: ………………………………………………

9) In the past, how often you have used Self Check-in Kiosk (SCK) in your travel experience:

I never saw them ☐ I only used them a few times ☐
I looked at them but never used them ☐ I frequently use them ☐
I always use them ☐

Table A.2. Survey Questions: Measuring Items

Dimensions (# items)	Questions	Source
Effort Expectancy (4 items)	**EE1**- learning how to use SCKs is easy for me **EE2**- My interaction with SCKs is clear and understandable **EE3**- I find SCKs easy to use **EE4**- It is easy for me to become skillful at using SCKs	UTAUT2 Model (Venkatesh, Thong, & Xu, 2012)
Performance Expectancy (3 items)	**PE1**- I find SCKs useful in my travel experience **PE2**- Using SCKs helps me check in to my flight quickly **PE3**- SCKs simplify my travel experience	UTAUT2 Model (Venkatesh, Thong, & Xu, 2012)
Social Influence (3 items)	**SI1**- People who are important to me think that I should use SCKs for checking in to my flights **SI2**- People who influence my behavior think that I should use SCKs for checking in to my flights **SI3**- People whose opinions I value prefer that I use SCKs for checking in to my flights	UTAUT2 Model (Venkatesh, Thong, & Xu, 2012)
Facilitating Conditions (3 items)	**FC1**-I have the knowledge necessary to use SCKs **FC2**- SCKs is compatible with other technologies I use **FC3**- I can get help from others when I have difficulties using SCKs	UTAUT2 Model (Venkatesh, Thong, & Xu, 2012)
Hedonic Motivation (3 items)	**HM1**-Using SCKs is fun **HM2**-Using SCKs is enjoyable **HM3**-Using SCKs is very entertaining	UTAUT2 Model (Venkatesh, Thong, & Xu, 2012)
Functionality (5 items)	**FU1**- I can get my check-in done with the airport's SCKs quickly. **FU2**- The service process of the airport's SCKs is clear **FU3**- Using the firm's SCKs requires little effort **FU4**- I can get my check-in done smoothly with the airport's SCKs **FU5**- Checking in with SCKs is error-free	SSTQUAL Model (Lin & Hsieh, 2011)
Enjoyment (3 items)	**EN1**- The operation of the airport's SCKs is interesting **EN2**- I feel good being able to use the SCKs for checking in **EN3**- Checking in with SCKs has interesting additional functions and features	SSTQUAL Model (Lin & Hsieh, 2011)
Security (2 items)	**SEC1**- A clear privacy policy is stated when I use the airport's SCKs **SEC2**- I feel safe when using the airport SCKs	SSTQUAL Model (Lin & Hsieh, 2011)
Assurance (3 items)	**ASU1**- The airport's reputation affects my decision to use SCKs **ASU2**- The reputation of the airline that I am flying with affects my decision to use SCKs **ASU3**- The reputation of the city where that airport is located affects my decision to use SCKs	SSTQUAL Model (Lin & Hsieh, 2011)

Table A.2. (cont.)

Perceived Risk (3 items)	**PR1-** I hesitate to use SCKs for fear of mistakes I can not correct **PR2-** I feel nervous about using SCKs **PR3-** I fear losing my flight due to my careless mistakes in using SCKs	(Curran & Meuter, 2005a)
Behavioral Intention (3 items)	**BI1-** I will use SCKs provided by airports in my next flight **BI2-** I will talk positively to people around me about using SCKs for checking in their flight **BI3-** The probability that I will frequently use the SCKs offered by airports in the future is high	UTAUT 2 Model (Venkatesh, Thong, & Xu, 2012)

APPENDIX B

Evrak Tarih ve Sayısı: 08.02.2024-36783

T.C.
İBN HALDUN ÜNİVERSİTESİ
Sosyal ve Beşeri Bilimler Bilimsel Araştırma ve Yayın Etiği
Kurulu Başkanlığı

Sayı : E-71395021-050.04-36783 08.02.2024
Konu : Etik Kurulu Kararı - Misagh Haji AMIRI

İLGİLİ MAKAMA

Kurulumuza başvuran Misagh Haji AMIRI'nın "Factors Affecting User Behavioral Intention to Adopt Self-Service Kiosks in Airports: A Structural Equation Modeling (SEM) Approach" isimli projesi; amaç, araştırma türü, veri toplama araçları, süreç ve işlemler, veri analizleri dikkate alınmak suretiyle 18.01.2024 tarihinde değerlendirilerek 2024/01-01 karar numarası ile etik açıdan uygun bulunmuştur.
Bilgilerinizi arz/rica ederim.

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