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Understanding IoT Mobile Payment Adoption: An Incorporating the UTAUT Theory with the Trust Acceptance Model

Ali Alkhalifah
Department of Information Technology
College of Computer
Qassim University, Buraidah, Saudi Arabia
a.alkhalifah@qu.edu.sa

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Abstract. A customer enters a store, buys something, and leaves without realising that the customer has been charged. This trend is significantly growing due to the increasing availability of NFC, Bluetooth, and/or Internet of Things (IoT) enabled devices for payment. IoT-based mobile payment solutions have significant potential to address increased consumers' desire for convenience and improve efficiency. Nevertheless, the adoption of IoT mobile payment systems is still in its infancy. Hence, this study examines the factors driving consumers' behavioural intention to use IoT mobile payment by employing the theoretical lens of the unified theory of adoption and use of technology (UTAUT) and trust-based acceptance models. This research applies a structural equation modelling (SEM) analysis and the PLSpredict algorithm to validate the model. Based on data collected from university students and faculty members due to their high probability of using IoT mobile payment systems, this work reveals an excellent tendency to adopt online and mobile payment. The findings highlight the three most influential factors (i) performance expectancy, (ii) effort expectancy, and (iii) trust. Moreover, this study discloses a high correlation between cognitive and emotional trust and trust within the trust-based acceptance model. However, the result reveals insufficient statistical evidence to support the positive impact of social influence, facilitating condition, and price value on consumers' behavioural intention to use IoT mobile payment. Finally, this study offers practical and theoretical implications in the IoT and mobile payment literature.

Keywords: Mobile Payment, IoT, UTAUT, Trust, Behavioural Intention, Adoption.

1. Introduction

The rapid development of novel technologies solutions and innovation is frequently described as the 4th Industrial Revolution, which brought about numerous social and economic changes worldwide [1]. Industry 4.0 is characterised by the rapid adoption of the Internet of Things (IoT), big data, smart devices, artificial intelligence (AI), and machine learning (ML). These technological solutions transform every aspect of human life and unrelentingly advance business processes and manufacturing methods. The business transactions and commerce industry has appeared to be critical adopters of the 4th Industrial Revolution. This is due to incorporating several Industry 4.0 concepts to considerably improve business purchases [2], reshaping business models and their entire ecosystem. Hence, this study focuses on one of the primary 4th Industrial Revolution, known as the IoT-based mobile payment, and discusses its significance in the present-day business transaction. Specifically, the study examines IoT mobile payment adoption from the client's standpoint and examines the critical adoption determinants.

The IoT refers to a global network made up of any object, as regularly described as thing, that may be implanted in any environment to capture data and transmit it over the Internet to another site which can be used for analysis or storage [3,4]. Moreover, A study [1] lamented that the phrase "things" introduces a new degree of interaction between human and application by enabling objects and people to exchange information via some connection in real time. Hence, the interconnected device networks have the potential to allow a plethora of intelligent as well as autonomous applications and numeraour services with considerable economic, professional, and personal benefits [1,5].

Reports suggest that more than 10 billion active IoT devices are expected in 2021, and the number of active IoT-based devices is estimated to exceed 25.4 billion by 2030 [6]. The IoT industry is booming, as almost 40% of the industry leaders claim that their firms are already deploying IoT solutions. It is also expected that this industry will have a 22% growth within the next two years. Additionally, the IoT investment will increase, with 40% of firms expected to boost spending on IoT solutions between 2020 and 2021 [6]. Hence, the anticipated increase in IoT deployment is expected to affect transactions massively. According to Holst [7], the IoT is advancing globally at a breakneck rate, and this market is valued at around $389 billion in 2021, and in 2030 it is predicted to reach one $trillion. This revenue projection includes shipments of embedded and smart systems, infrastructure, connectivity services, security solutions, professional services, purpose-built IoT platforms and applications, and analytics [8].

Similarly, the growth of proximity payment has constantly been increasing. Enberg [9] from eMarketer reported that 36.3% smartphone users are predicted to make at least one in-store mobile payment per six months. Although almost all the users are predicted in Asia-Pacific countries, especially China with the highest number of worldwide consumers for the proximity mobile payment. Furthermore, it is indicated that proximity mobile payments are common among smartphone users in Denmark, South Korea, India, and Sweden [9]. Figure 1 shows the breakdown of global users of proximity mobile payment. Nevertheless, mobile payment adoption rates are more significant in nations where other electronic payment methods, like credit cards, are unavailable. In contrast, the adoption rates of mobile payment are lower in countries where consumers have access to a robust financial infrastructure and various credit cards options such as the United States and Canada [7]. Hence, reference [6] noted that understanding the factors contributing to the growth of IoT adoption vis-à-vis IoT-based mobile payment is needed.

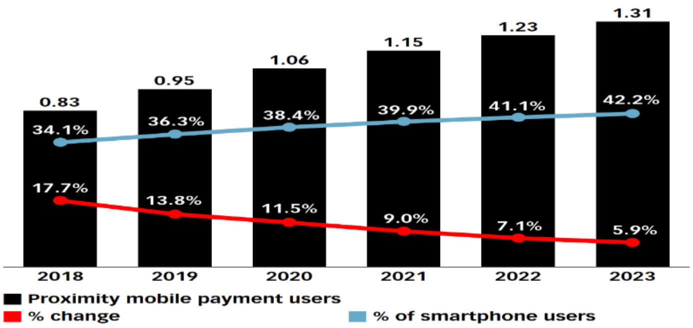

Fig.1: Usage of Proximity Mobile Payment Worldwide [9]

Due to economic and social consequences, transaction, access, and ticketing are among the most promising IoT applications [10]. Significant technological advancements from hardware and software components are necessary to produce consistent, effective, safe, adaptable, timely, energy-efficient, and patient-centred payment systems. The concept of IoT-mobile payment generates considerable anxiety, especially if the risk of losing money is involved. This offers new motivation for research and inquiry. Yet, the concern is whether consumers will feel comfortable using this technology [11]. Therefore, this study fills a research gap by examining factors that could influence the IoT mobile payment adoption from the consumers' perspectives. This is because there is a disconnect in the academic literature regarding the IoT mobile payment adoption from this perspective, as most existing research focused on the organisation. Nevertheless, and to the best of our knowledge, Li & Li [12] is the only study that investigates third-party mobile payment user satisfaction under the umbrella of IoT environment. As a result, the central research question of this study is how do technology adoption factors IoT-based mobile payment adoption? This study investigates factors influencing the consumers' adoption of IoT mobile payment by using the theoretical lens of the unified theory of acceptance and use of technology (UTAUT) and the trust-based acceptance model. Hence, the following points summarize the contributions of this stusy to the existing knowledge :

This study is one of the first empirical study to examine IoT mobile payment adoption.

It utilises and integrates the UTAUT and trust-based acceptance model to in the context of IoT mobile payment adoption, which is lack in the literature.

It explores trust and its multi-dimensional constructs as a significant factor for IoT mobile payment adoption, which has been limited in existing mobile payment studies.

The paper is structured based on a typical empirical study design. In particular, the following section covers the brief literature on mobile payment and IoT integration and adoption to establish the background to study IoT mobile payment. Section 3 covers the conceptual model, and Section 4 discusses research methodology; section 5 demonstrates the result, Section 6 and Section 7 provides discussion and Limitation and Future Directions, respectively, and concludes this study.

2. Literature Review

Several studies have been done to investigate IoT [8]. However, only a recent study by Li and Li [12] reported a combination of IoT and mobile payment and used third-party mobile payment user satisfaction under the umbralla of IoT environment. Hence, to establish motivational justification and link with previous research, this study divides the literature into different topics, such as mobile payment adoption, IoT adoption, and IoT mobile Payment. This provides rationale on to why this study is grounded based on both theory and practical application.

2.1 What is a Mobile Payment and its Relationship with IoT?

Firstly, Lin et al. [13] recently described mobile payment as a type of payment used to purchase bills, invoices, goods, and services. Another study defined mobile payment as a paradigm of payment that utilises electronic means to complete transactions [14]. Globally, mobile payment is employed, enabling consumers to conduct online transactions at any time and location [15], enhancing domestic and international trade [16,17]. With the rapid advancement of technology, the mobile payment's appeal is primarily due to its flexibility and ease [18]. Furthermore, mobile payment falls under the electronic payment that allows mobile users to purchase through users device connecting to the internet and utilising communication technology [19]. Mobile payments improve the convenience of online transactions. Previous research has found that the amount of time required to consume mobile services and the inde- pendence of consumption sites are important factors impacting mobile technology and services [20,21]. As a result, improved usability increases users' desire to use mobile payment [22–25]. Therefore, mobile payment is a term used to describe a transaction that is at least partially completed using a mobile device (such as a smartphone, mobile phone, PDA, or any other supported wireless network device) [26]. A mobile network and wireless technologies such as RFID, NFC, and Bluetooth are used to safely execute the financial transaction. Point-of-Sale (POS) transactions done with a mobile phone as a payment method are also known as POS mobile wallet payment and POS mobile contactless payments, which comprise scanning, swiping, or tapping a mobile phone at the POS to complete a transaction [27]. As a result, the concept of money transfer is included in all definitions of mobile payments [13].

Interestingly, the global mobile payment market is projected to reach 3695.46 billion USD by the end of 2024 [28]. This expectation is based on the volume of mobile payment transactions which witnessed an increase of 106 billion USD in 2020 globally. Indeed, worldwide mobile phone users are anticipated to reach 7.49 billion USD in 2025, while global smartphone users are approximated to jump 7 billion USD [29]. In addition, the number of international mobile payments users is predicted to exceed 1.3 billion USD by 2023 [30]. In 2020, it was estimated that there are 720 million members of mobile payment [31]. Given that any mobile commerce transactions' success entails mobile payments, it is critical to evaluate the factors associated with mobile payments. Most mobile payments, have been performed via NFC [32], a secure and safe technology that allows devices to transmit small amounts of data over extremely short distances. Because of the small distance, it's difficult for a transaction to be charged to the wrong person or hijacked by a third party. Furthermore, payments performed with NFC are quick and simple. The amount is displayed on an NFC-enabled terminal or POS, and the consumer touches it with their smartphone or NFC-enabled smartwatch to complete the transaction in a second [27]. Bluetooth's contribution to electronic payments appeared to be confined to allowing restaurants to bring mobile terminals to their customers' tables to collect card payments, but then beacons arrived [32]. In contrast, Bluetooth has been a part of telephones before integrating mobile companies. Apple and Google ultimately picked NFC technology for their payment wallets. On the other hand, Bluetooth offers several natural benefits that may make it a formidable option. For example, Bluetooth has a far greater range than NFC, allowing

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transactions to be done without needing users to wait to use a station terminal. Additionally, Bluetooth has far higher bandwidth and supports one-to-many communication in contrast, NFC is a one-to-one technology. Remarkably, the bluetooth technology may also be readily linked into a beacons system used to determine a customer's location and alert them to special offers. Not only are beacon-based mobile payments proving to be effective, but they are also proving to be beneficial in terms of brand loyalty, as they enable brands to communicate directly with customers. Additionally, the most advantageous system may neither be one nor the other, but both motivate the development of a hybrid solution [32]. According to Apple's patent filings, one system uses NFC to establish the link but subsequently switches to Bluetooth to execute the transaction. Thus, much more data, coupons, receipts, and loyalty cards may be communicated without the client needing to hold their phone against the terminal for an extended period. Ultimately, a combination of technologies may result in the world's most accessible payment system. Customers enter a store, selects what they want, and exits without being aware that they have been charged. This may seem farfetched, but with today's technology, anything is doable. Mobile payment growth is potentially enormous due to the rising availability of NFC, Bluetooth, and/or IoT-enabled devices. The only valid constraint is the ability to convince clients to accept and adopt them. Figure 2 presents the IoT-enabled mobile payment ecosystem. Moreover, reference [33] assert that NFC is the successor to RFID, the primary driver of IoT development. However, NFC is similar to RFID, but it offers enhanced security and functions.

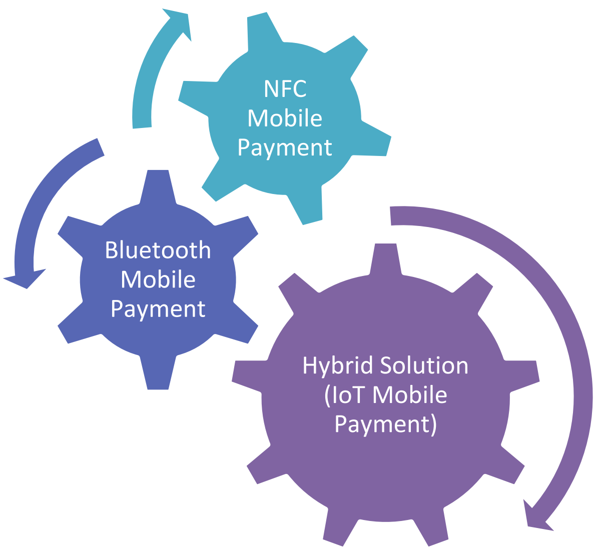

Fig.2: IoT Mobile Payment Ecosystem

2.2 Review of Mobile Payment Adoption

The work by [24] carried out a survey study on mobile payment, highlighting that prior literature revealed many studies on mobile payments. The authors reported that the focus of most of these works was not the adoption or acceptance of mobile payment adoption. Although there are few studies that focuses on the mobile payment acceptance or adoption. Specifically, study by [19] assessed 73 articles on mobile payments. In addition, reference [34] extended the research work by [19] on mobile payment by examining an additional 188 studies. Accordingly, the studies did not focus exclusively on consumer adoption of mobile payments but rather on many categories of mobile payment research, one of which was mobile payment adoption [24]. In the earlier work, the study concluded that the most dominant theories are the technology adoption model (TAM), the diffusion of Innovation (DOI), as well as the unified theory of acceptance and use of technology (UTAUT). The later work reported additional theoretical models such as the task-technology fit (TTF) theory, the theory of reasoned action (TRA), and the theory of planned behaviour (TPB), based on the analysis of 34 studies on mobile payment adoption [34]. From this literature, it is evident that TAM and UTAUT are dominant theories in the mobile payment adoption domain [24,34], as this encourages the introduction, integration, or extension of new theories to understand new knowledge, which has been revealed from the previous approaches. The authors stated that studies conducted after 2007 lacked creative constructs and proposed that researchers studynmobile payment acceptance using theories other than TAM and UTAUT [34].

Moreover, another review focused on mobile payment adoption using theoretical models and hypotheses and identified 57 studies on mobile payment uptake from 2014 to 2018 [35]. Similarly, the work reported TAM, UTAUT/UTAUT2, and DOI as the most often used theories. The study highlighted that the TAM and UTAUT had remained the most frequently employed, identifying the importance of developing new theoretical models for studying mobile payment acceptance or adoption. The work by [24] demonstrated numerous distinctions among technology adoption models, with the majority relying on distinct theories such as TAM, DOI, and UTAUT. However, existing studies are lacking in integrating trust models in the recent literature. Nonetheless, reference [36] utilised DOI within a valence framework and discovered substantial connections, with the trust variable found to be more significant than risk. Similarly, Gao and Waechter [37] used the valence framework and integrated TAM to examine initial trust rather than risk. The researchers discovered a statistically significant connection between initial trust and perceived reward.

In addition, Park et al. (2019) [38] proposed a model based on trust, risk, benefit, and intention constructs. However, the authors did not refer to their proposed model as valence frameworks. All outcomes except for the benefit to intention were statistically significant. Remarkably, the literature has only identified the integration of a trust-based acceptance model, based on [39] and [28] studies, which incorporate cognitive and emotional trust variables in their proposed models. These are the limited studies regarding mobile payment adoption that used a trust-based acceptance model with cognitive and emotional variables, which investigate the trust of mobile commerce with a focus on payment [28] and trust transfer from online to mobile payments services adoption [39].

Based on the literature, it is interesting to note that the studies utilising the trust- based model and any dominant adoption model are lacking from the IoT mobile payment perspectives. Additionally, the review discovered that cognitive and emotional trust had been investigated as mobile payment adoption factors. Several studies explored trust as a construct for mobile payment acceptance or adoption [24]. Each framework used a distinct set of theoretical models and antecedents. The majority of works addressed the concept of trust as a single-dimensional factor [24,40]. Also, this study answers Dahlberg et al.'s [34] call, introducing and integrating novel theoretical approaches to examine mobile payment adoption or acceptance.

2.3 Review of IoT Adoption

Recently, Arfi et al. [1] raised concerns about the scarcity of quantitative research regarding IoT adoption. Similarly, when researchers examine IoT adoption, they frequently reference the technology acceptance model, the UTAUT model, as well as the task-technology fit model (TTF). However, several limitations have been reported widely. For example, many studies have demonstrated that classic acceptance models can be augmented with new features such as fun and enjoyment [34,41]. Trust has been shown to influence how beneficial IoT technology is viewed [37,41]. Kim et al. [42] make an effort attempt to extend the TAM using the value-based adoption model (VAM). Hence, the authors investigated how customers adopt intelligent home services and examined VAM functions based on rewards (usefulness, enjoyment, and variety seeking) and then sacrifice (technicality and perceived fee). The characteristics are seen as determinants of perceived value and, consequently, customers' motivation to use technology.

Hsu and Lin [43] proposed a novel method for examining IoT adoption. The study analysed consumers' motivations to use IoT in terms of privacy concerns and network externalities. The authors described network externalities; "the value or effect that users derive from a product or service that increases in value when users, complementary products, or services increase" [44]. The perceived benefits are critical in understanding why users behave in specific ways regarding IoT services. The perceived compatibility and perceived critical mass both have a significant effect on perceived benefits. Additionally, the study found that consumers' intentions to use IoT are less affected by privacy issues than perceived benefits.

Furthermore, the study by Hoffman and Novak [45] examined IoT adoption, which concluded that the distinct characteristics of IoT products interact with customers and generate a unique experience and meaning for each other, as each consumer mixes (or assembles) smart objects differently. To foster a more nuanced knowledge about consumer experience, the study proposed a conceptual framework using DeLanda's assemblage theory, connecting object experience and customer. Furthermore, Caputo et al. [46] used motivation theories to investigate the relationships between the factors that influence customers' motivations and decisions to use IoT-based solutions. Extrinsic motivators, such as entertainment and social contact, and intrinsic motivators,such as knowledge acquisition, privacy risk, and technological readiness level, were chosen as characteristics of the researchers' model. Customers' propensity to utilise IoT devices can be influenced by entertainment, information learning, social connections, and technological readiness, according to the study.

In addition, Kim's work [47] is notable for employing a psychology and user-experience approach to investigating human–IoT interactions, which aimed to find elements that can contribute to the value of the IoT experience for customers. The author used the concepts of computers as the modality and social actors , interactivity, agency, and navigability model of technology impacts to develop the study concept, which is whether IoT devices may be viewed as a technological sources rather than just communication channels. Thefore, the study revealed that source attribution (utilising information from single or multiple sources) is critical in defining human–IoT interaction quality. The study demonstrated that those psychological elements significantly impact IoT's technological components.

In addition, Jayashankar et al. [48] investigate IoT adoption among US farmers using consumption value theory. In their model, the authors looked at how risk and perceived value affect IoT adoption, as well as how trust incorporates both perceived value and risk. According to the findings, trust improves perceived value while lowering perceived danger. Additionally, the perceived risks of personal data misuse can have a detrimental effect on IoT adoption.

2.4 IoT Mobile Payment

In summary, this study classifies mobile payment under the umbrella of the IoT environment. Accordingly, recent work by Li & Li [12] presented the concept of third-party mobile payment, as shown in Figure 3. Moreover, IoT mobile payment is a solution of mobile payment conducted via IoT-enabled devices and interlinked networks such as smartphones, smartwatches, etc. Existing litretaure reveals that researches on IoT adoption have evolved in two distinct directions in recent years [1]: (i) seeking new ways to improve established models and (ii) developing new approaches based on consumer psychology, human-technology interaction, and conceptualising the concept of customer experience, among other factors. In contrast, the traditional models are still dominating in this research field.

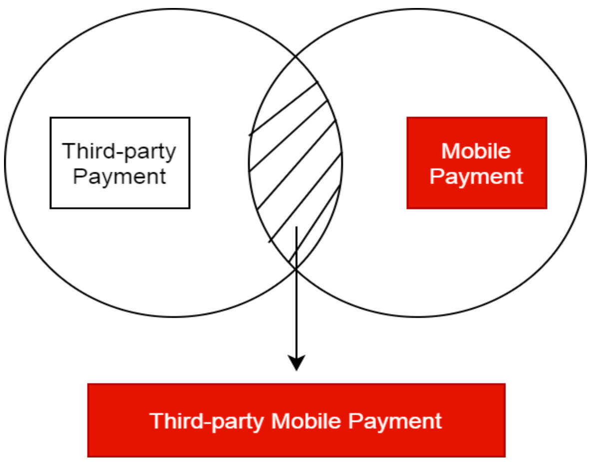

Fig.3: Third-party payment, mobile payment, third-party mobile payment relationships.

3. Conceptual Model

3.1 Unified Theory of Acceptance and Use of Technology (UTAUT)

Venkatesh et al.[49] compared eight competing adoption theoretical models to understand technology adoption. The eight competing adoption theoretical models were (i) the theory of reasoned action (TRA), (ii) TAM and TAM2, (iii) TPB and DTPB, (iv) combined TAM and TPB, (v) IDT, (vi) the motivational model, (vii) model of PC utilisation, and (viii) social cognitive theory. Based on 215 respondents from four different organisations, the longitudinal investigations combined and elaborated the eight theoretical models to create a new model, termed unified theory of acceptance and use of technology, abbreviated as UTAUT. Not only does the UTAUT model highlight the primary predictors of intention to adopt, but it also enables researchers to assess the contingencies of moderators that would amplify or diminish the effects of those determinants. Moreover, the UTAUT model has been empirically confirmed and demonstrated to be superior to other models [49-51]. As a result, the UTAUT model has been cited as one of the main ideas in the literature on technology adoption in various cases [24,34]. It is used as the theoretical framework for constructing the research hypothesis.

The UTAUT model includes four key components: effort expectancy, performance expectancy, facilitating conditions, and social influence, whereas the UTAUT2 added price value, hedonic motivation, and habit [52]. These factors have an impact on a person's willingness to utilise technology and/or their actual use of technology. The components and concepts of the UTAUT model are applied to the setup of IoT mobile payment behavioural intention in this study. According to the UTAUT model, performance expectancy, effort expectancy, and social influence drive behavioural intention to use technology, whereas behavioural intention and facilitating conditions determine technology use. The UTAUT model was created to investigate workplace technology adoption. This model was also extended to look into the factors that influence people's adoption of innovations in different situations (Venkatesh et al., 2012). Contextual variables allow for a more precise evaluation of user acceptability of technology, which is always domain-specific [52,53]. The UTAUT paradigm has been widely used to focus on user intention and behaviour in technology adoption and diffusion since its inception. According to Williams et al. [54], the UTAUT model successfully harmonised the literature on technology adoption due to its connections to eight other technology adoption models.

This study uses the UTAUT model due to its validity in previous research on mobile payment and IoT adoption with the exception of hedonic motivation and habit constructs, as these variables have been validated for mobile payment and IoT adoption [13,35,55,56]. Additionally, some authors have called for more research to investigates the broader application of IoT solutions based on relevant technology adoption theories [1,24,34]. This encompasses broadening the scope of the UTAUT to integrate additional variables and investigate diverse topics that have been neglected and deserve significant attention. However, the study of the UTAUT model observed in various studies reveals that the most typical drawback is a narrow emphasis on a specific issue, such as a country, community, organisation, , department, culture, agency, or age group [1]. This study overcomes these constraints by collecting data in the Kingdom of Saudi Arabia (KSA), a country and community that is cultural and gender-sensitive and focused on IoT payment that is domain-specific with an additional construct known as price value.

3.2 Trust-Based Acceptance Model

Trust is a critical element of every transactional activity and is described as “the readiness of one party (trustor) to rely on the acts of another party (trustee)” [57]. The trust-based acceptance paradigm originated from scholars’ past use of the theory of reasoned action (TRA) [58] to analyse IT adoption. Komiak and Benbasat [59] developed a trust-based acceptance model based on TRA by analysing how emotional and cognitive trust promotes e-commerce reliance. Moreover, cognitive trust is defined as a trusting belief focused on the trustor’s opinion that the trustee possesses specific attributes (i.e., compassion, integrity and competence) that can be relied upon [60,61]. Additionally, emotional trust is characterised as affective trust, a form of trusting attitude indicated by the trustor’s attitude and emotional states toward the comfort and security associated with trusting the trustee [62].

Unlike traditional mobile payment, where trust is established through transactional experiences, IoT mobile payment establishes trust through customers’ interactions with the IoT environment [12,28].. Two trust components develop confidence (i) cognitive and (ii) emotional trust [62,63]. Cognitive trust is caused by interest and self-perception in performance and successes based on reasonable appraisal, sound reasoning, and available knowledge in the interactions with vendors [64]. On the other hand, cognitive trust can be established through the suppliers’ features such as professional credentials, familiarity, and reliability. The emotional trust is built by establishing social-emotional ties that extend beyond a routine commercial engagement.Therefore, it is based on emotional relationships and attachments between clients. Strong positive feelings toward an object of trust may inspire trust more than sound intellectual thinking or a combination of the two[65]. As a result, this study chooses the trust-based acceptance model [59] as the theoretical framework to integrate with UTAUT, as it combines cognitive and emotional trust.

Furthermore, cognitive trust differs from emotional trust in that it is founded on reasonable assessments of the trustee’s qualities. Emotional trust, on the other hand, is the psychological security that allows users to feel at ease and confident in trusting the trustee despite the lack of immediately available evidence [59]. When a trustor recognises and believes in substantial logic, cognitive trust is built, whereas emotional trust is established only on the basis of consumer sentiments [62]. In online situations, consumers evaluate trustworthy behaviour effectively, and if they have a high level of emotional trust, they will actively engage in particular behaviours [66]. Finally, this study regards emotional trust as a crucial component because, without emotional trust, the ability to comprehend consumers’ behaviour selections can be hindered [59].

3.3 The rationale of the Integrated Research Model

This study chooses the trust-based acceptance model to acquire a more profound knowledge of the trust-building process in IoT mobile payment. The study considers the trust-based acceptance model as one of the elements of the combined research model. Given that mobile payment is used to perform transactions, it is reasonable that consumers' cognitive and emotional trust in mobile payment is employed as a source of trust in IoT mobile payment. Additionally, this study incorporates the UTAUT model as one of the dominant models that were originated from eight different technology adoption theories and considering several assertions from the literature regarding its superiority to other models [49–51]. Thus, this study believes that technology adoption factors could influence consumers' mobile payment adoption. Through this integrated research method, as presented in Figure 3, this study also offers a sophisticated understanding of what factors contribute to the adoption of IoT mobile payment.

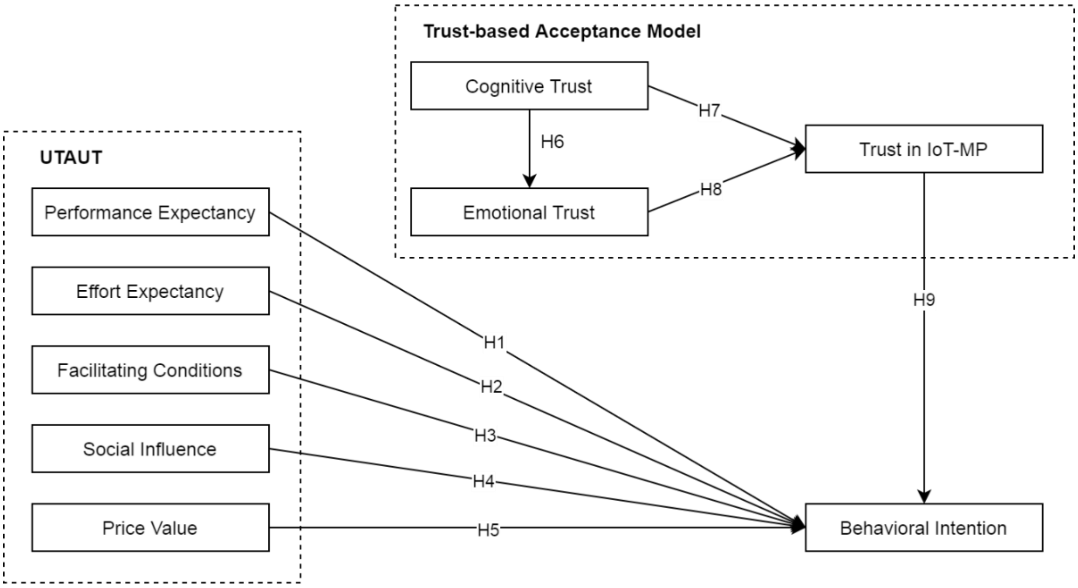

Fig.4: Research Model and Hypotheses.

3.4 Hypotheses Formulation

To empirically examine the between research variables as well as their impact on behavioural intention toward IoT mobile payment, a conceptual model based on the UTAUT model described in the literature review is integrated with trust-based acceptance model is developed. The trust-based model covers cognitive and emotional trust. Thus, the variables are all predictors of the intention to utilise IoT mobile payment in the hypothesised model. The outcome variable is the behavioural intention to adopt IoT mobile payment, while trust is a mediator between cognitive and emotional trust. The conceptual research model and the hypotheses about the relationship between the research constructs are discussed as follows. Similarly, the dependent variable is a behavioural intention, which refers to the extent to which technology or any associated object/device is intended to be used by end-users or consumers [49].

Performance expectancy (PE) refers to the degree to which adopting a technology improves users' effectiveness when doing specific tasks [52]. Effectiveness could be defined in the context of IoT mobile payment as the degree to which the technology assists users in making payment without using other payment facilities, which could be time consuming. Thus, PE refers to how an individual believes that the system will improve the end user's transactions experience. Increases in end users' perceptions of the PE of connected IoT devices, such as improved payment management, improved access to other services, and enhanced overall quality of life, all have a favourable effect on end users' behavioural intention to adopt IoT mobile payment [13]. As a result, the study proposes the following hypothesis.

H1: Performance expectancy has an effect on behavioural intention to use IoT mobile payment.

Effort expectancy (EE) is a term that relates to "the degree of ease with which a system can be used" [49]. When it comes to the initial usage of technology, such as accepting an innovation, the degree of convenience connected with that technology significantly impacts the adoption behaviour [67]. As a result, the degree to which consumers perceive technology to be simple to use affects their assessment of its usefulness, making effort expectation the forerunner to perceived benefit [23,68].. In the context of end-user use of IoT mobile payment, EE is associated with an increase in a technology's perceived benefit and usefulness. As a result, increased EE refers to the energy spent when using the IoT mobile payment. As a result, the study proposes the following hypothesis.

H2: Effort expectancy has an effect on behavioural intention to use IoT mobile payment.

The term "facilitating conditions" (FC) refers to technological resources and infrastructure to help people adopt the technology. Numerous research has been conducted to determine FC's impact on consumers' adoption [69–71]. Conducive settings may have a beneficial effect on consumers' behavioural intention to use IoT devices. Additionally, prior research has established a link between the availability of technology resources and technical infrastructure and their intention. Several studies claim a positive relationship between FC and behavioural intention [13,72,73]. As a result, the following hypothesis is formulated to investigate this relationship on the adoption of IoT mobile payment.

H3: Facilitating conditions has an effect on behavioural intention to use IoT mobile payment.

Social influence (SI) refers to the extent to which an individual values the opinions of peers while deciding whether or not to use a new system [49]. The literature regarding predicting users' behaviour of technology adoption in mobile payment has established that SI is a crucial predictor, as family and friends' opinions strongly influence user behaviour [13,23]. Also, numerous studies have demonstrated the significant influence of SI in adopting new technology [70-72]. Thus, the following hypothesis is formulated to test the relationship between SI and IoT mobile payment behavioural intention.

H4: Social influence has an effect on behavioural intention to use IoT mobile payment.

The financial cost that represents consumers' cognitive trade-off between perceived benefits of mobile services and the monetary cost of those services is referred to as price value (PV) [52]. PV helps offset the costs of data service providers (mobile internet), the device itself, and, when necessary, service charges. Previous study has found that perceived financial expenses act as a deterrent to the use and adoption of mobile services [74,75]. Consumers have several challenges to adopting IoT products/services, according to some studies, because the IoT is a novel idea for them [76]. As a response, potential customers who are uninformed of the value that the Internet of Things could give may be unwilling to pay high rates and see financial costs as a barrier. To study the correlation between PV and behavioural intention, the following hypothesis is proposed.H5: Price value has an effect on behavioural intention to use IoT mobile payment.

As stated previously, the trust-based acceptance model is integrated within this study to understand the predictors of IoT mobile payment more broadly. Thus, following the theoretical lens of the trust model, trust in IoT is assumed to be the source of trust in mobile payment. Accordingly, there are two predictors of trust following the trust-based acceptance model, including cognitive trust and emotional trust.

The relationship between emotional trust (a trusting attitude) and cognitive trust (a naive belief) conforms to trust, and then behavioural intention exists based on TRA theory [58,66]. Similarly, there is a correlation between cognitive and emotional trust in online services [77]. When consumers believe that relying on agents will result in accurate and well-tailored recommendations (i.e., cognitive trust), they will feel highly confident about sending information to this agent (i.e., emotional trust). Sun [62] contended that cognitive trust in the middleman and a buyer affects emotional trust. Several studies [28,39,78] asserted that cognitive trust in mobile payment is connected with emotional trust. As a result, this study anticipates that cognitive trust in IoT mobile payments will affect emotional trust in mobile payments as well, as indicated in the following hypothesis:

H6: Cognitive trust has an effect on emotional trust in IoT mobile payment.

Recently, Leong et al. [28] adopted a trust-based acceptance model to study mobile commerce and highlighted that cognitive trust in mobile payment services is defined as consumers' expectations that the properties of mobile payment services are trustworthy [78]. Cognitive trust in mobile payment is connected with an increased likelihood of adopting mobile payment [36,79]. According to a study [80], cognitive trust is connected with continued smartphone use. On the other hand, emotional trust in mobile payment refers to consumers' sentiments of comfort and security when making mobile payments [78]. Emotional trust in mobile payment is associated with utilising mobile payment [60]. Idemudia et al. [81] asserted that emotional trust in cellphones is related to their continued adoption.

Chen and Wang [82] validated that trust may be transferred from electronic commerce to social commerce using the trust models. According to Chu and Yao-bin [83], trust in online banking can be transferred to mobile banking. Similarly, Gong et al. [78] observed that consumers' emotional and cognitive trust in online payment might be transferred to mobile payment due to their perception of a tight relationship between both channels. Additionally, Lin et al. [84] argue that intra-channel trust can be transferred when customers' faith is transferred to another entity within the common channel. Typical mobile payment operates in the IoT environment. This study believes that consumers' trust in IoT mobile payment could affect behavioural intention. As a result, this study hypothesised the relationship as follows;

H7: Cognitive trust in IoT mobile payment has an effect on trust in IoT mobile payment.

H8: Emotional trust in IoT mobile payment has an effect on trust in IoT mobile payment.

Additionally, the research model also intent to determine the effect of trust on the behavioural intention of IoT mobile payment. When consumers use mobile payment systems to transfer money or make purchases , there are levels of danger involved, for example, losing personal funds. By mitigating the risk, a consumer may place their faith in the merchant. For instance, a negative relationship is envisaged in which a consumer perceives less risk if they enhance their trust, for example, by transacting with a trusted provider. Hence, the more consumers trust their mobile payment platforms, the less risky the medium appears to them, and the greater their desire to adopt it. Numerous research on mobile payment adoption has indicated that trust has an important influence association with the intention to adopt mobile payment system [85]. Thus, the following hypothesis is formulated to investigate the relationship between trust and IoT mobile payment behavioural intention.

H9: Trust has an effect on behavioural intention to use IoT mobile payment.

4. Research Methodology

This study employed Qassim university students and faculty members as participants from the Kingdom of Saudi Arabia (KSA). This sample is selected based on several reasons. First, it has been argued that students and faculty members are more likely to adopt online and mobile payments [39]. Second, higher education people tend to reveal a good tendency of using innovative and emerging technologies such as IoT mobile payment [86]. Third, a report showed that IoT usage is mainly common among individuals with higher education backgrounds [87]. Finally, the selected sample has been used in previous mobile payment literature [24,39]and e-commerce adoption studies [88]. For data collection, an invitation was sent by email to all the university' students and academic staff, containing the study description and the link to the survey.

At the beginning of the survey, a clear definition was introduced to define IoT in mobile payment and some payments modes (e.g., using a smartwatch or mobile phone to buy in person at the store) to better understand the context of the study. Subsequently, a filter question was asked to the respondents, indicating whether they are familiar with IoT mobile payment. During data preparation and cleaning, 40 responses were ruled out from the survey due to filter questions regarding familiarity with IoT mobile payment. Moreover, among 436 completed responses, 24 were removed as the subjects did not use IoT mobile payment before. Additionally, 12 responses were removed because they were invalid, either having the same answer to most questions (straight line issue) or having completed the survey in less than the average time (6 minutes). In total, 400 responses were considered suitable for further analysis. Hence, the sample size is fortunate enough to fulfil the criteria for conducting confirmatory factor analysis using PLS [89–91]. Among the total respondents, %53.3 were male, 46.7 % were females, 86.2 % were aged 30 or below. The majority of the subjects comprised students (%74), 94.2 % holding bachelor's degrees.

4.1 Measurement Items

Items scales were adapted from previous well-established studies that had already been tested and validated and modified to fit the purpose of the current research [92]. Although there is no fixed rule guiding how many items should be included in each item [93]. However, it is essential to ensure that the domain of each construct is sufficiently sampled. Reference [94] suggested that the total of three indicators loading on one common construct should statistically identify the factor measurement. Therefore, most constructs in the study were measured by at least three items (see Appendix A). Performance expectancy, effort expectancy, facilitating conditions, social influence,and price value measures were adapted from reference [49] and [13]. Cognitive trust, emotional trust were adapted from reference [39] and [28], and trust in IoT mobile payment was adapted from reference [24]. Behavioural intention items were adapted from reference [49], [13], and [24]. To capture the attitudinal measures of constructs, seven-point Likert scale ranged from "strongly agree" to "strongly disagree," with '7' being strong agreement and '1' being strong disagreement [93].

A pre-test stage was considered to refine and validate the survey questionnaire [90]. Five IS professors and ten students who are mobile payment services users were selected to seek their confirmation of the face validity of the survey questionnaire. Some modifications were conducted to address their suggestions.

5. Data Analysis and Results

Partial least squares were used to estimate the model using SmartPLS 3.0 software [95]. Confidence intervals were calculated using bootstrapping at 10000 samples [96]. For a concise description of the usage of partial least squares in information systems research, several reseaches were consulted in this study [38,89,97]. As indicated previously, the structural model was tested by determining the significance and effects of the hypothesised relationships.

5.1 Common Method Bias

Harman's single factor test was used to examine common method bias [98]; the result revealed that a single factor accounted for less than 37% of the variance in the measures, which is below the 50% suggested value [98,99]. Therefore, common method bias is not a concern for this study.

5.2 Measurement Model Assessment

The construct reliability of the measures was initially determined by analysing their convergent validity. As seen in Table 1, all item loadings are more than 0.700, specifically between 0.745 to 0.938, indicating that the items and their constructs share an acceptable amount of variation [89,97]. Table 2 summarises the reliability measures for the model's latent variables. Cronbach's alpha values are all greater than 0.70 and vary from 0.709 to 0.871. In addition, the Rho_A must be greater than 0.7 to indicate composite reliability, and this study Rho_A index ranges from 0.711 to 0.874. Similarly, the composite reliability (CR) are all greater than 0.80 and range between 0.839 and 0.911. Similarly, all the measures of extracted average variance (AVE) are larger than 0.50, ranging between 0.616 and 0.793 [89,97]. Remarkably, all these measurement indicators show that the measurement model is a good fit for the data.

Table 1: Item loadings and reliability measures

Construct	**Items**	**Standardized Loading**	**Cronbach's Alpha**	**rho_A**	**CR**	**AVE**
Performance Expectancy	PE1	0.827	0.871	0.874	0.911	0.720
	PE2	0.885				
	PE3	0.845				
	PE4	0.837				
Effort Expentancy	EE1	0.752	0.792	0.793	0.865	0.616
	EE2	0.823				
	EE3	0.808				
	EE4	0.754				
Facilitating Conditions	FC1	0.810	0.839	0.847	0.904	0.759
	FC2	0.938				
	FC3	0.861				
Social Influence	SI1	0.880	0.739	0.744	0.884	0.793
	SI2	0.901				
Price Value	PV1	0.775	0.805	0.812	0.886	0.722
	PV2	0.918				
	PV3	0.850				
Cognitive Trust	CT1	0.829	0.829	0.829	0.898	0.746
	CT2	0.897				
	CT3	0.864				
	ET1	0.768	0.709	0.711	0.839	0.635

Emotional Trust	ET2	0.872				
	ET3	0.745				
Trust_IoT-MP	TIM1	0.851	0.838	0.841	0.891	0.673
	TIM2	0.791				
	TIM3	0.827				
	TIM4	0.811				
Behavioural Intention	BI1	0.857	0.819	0.819	0.893	0.735
	BI2	0.890				
	BI3	0.824				

Table 2: Crossloadings of Measurement Items.

Construct	PV	FC	BI	EE	PE	SI	ET	TIM	CT
PV1	**0.775**	0.431	0.405	0.475	0.359	0.434	0.474	0.433	0.442
PV2	**0.918**	0.431	0.439	0.452	0.505	0.466	0.495	0.501	0.509
PV3	**0.850**	0.401	0.476	0.475	0.549	0.550	0.542	0.563	0.539
FC1	0.401	**0.810**	0.466	0.546	0.513	0.492	0.545	0.568	0.493
FC2	0.456	**0.938**	0.536	0.614	0.587	0.559	0.561	0.618	0.589
FC3	0.433	**0.861**	0.489	0.568	0.543	0.452	0.464	0.534	0.544
BI1	0.434	0.464	**0.857**	0.584	0.644	0.537	0.589	0.655	0.495
BI2	0.429	0.507	**0.890**	0.562	0.694	0.529	0.557	0.671	0.582
BI3	0.474	0.498	**0.824**	0.612	0.659	0.546	0.589	0.637	0.508
EE1	0.477	0.588	0.522	**0.752**	0.624	0.487	0.523	0.559	0.612
EE2	0.376	0.503	0.510	**0.823**	0.385	0.370	0.501	0.445	0.511
EE3	0.407	0.508	0.574	**0.808**	0.490	0.490	0.566	0.531	0.510
EE4	0.465	0.478	0.535	**0.754**	0.498	0.504	0.582	0.556	0.480
PE1	0.477	0.499	0.718	0.550	**0.827**	0.551	0.564	0.735	0.565
PE2	0.462	0.591	0.679	0.537	**0.885**	0.571	0.595	0.736	0.586
PE3	0.475	0.519	0.614	0.519	**0.845**	0.545	0.575	0.658	0.535
PE4	0.488	0.529	0.614	0.554	**0.837**	0.588	0.592	0.673	0.602
SI1	0.561	0.469	0.532	0.488	0.605	**0.880**	0.616	0.646	0.568
SI2	0.463	0.554	0.583	0.562	0.579	**0.901**	0.612	0.595	0.511
ET1	0.405	0.424	0.541	0.506	0.499	0.536	**0.768**	0.544	0.514
ET2	0.478	0.541	0.528	0.573	0.565	0.536	**0.872**	0.608	0.486
ET3	0.535	0.466	0.543	0.576	0.571	0.573	**0.745**	0.592	0.481
TIM1	0.524	0.552	0.703	0.566	0.725	0.627	0.630	**0.851**	0.570
TIM2	0.427	0.563	0.570	0.443	0.702	0.559	0.546	**0.791**	0.523
TIM3	0.469	0.519	0.635	0.554	0.653	0.544	0.644	**0.827**	0.497
TIM4	0.516	0.531	0.589	0.622	0.637	0.547	0.572	**0.811**	0.617
CT1	0.503	0.531	0.528	0.561	0.598	0.505	0.489	0.614	**0.829**
CT2	0.508	0.559	0.514	0.560	0.595	0.520	0.534	0.562	**0.897**
CT3	0.511	0.526	0.553	0.619	0.553	0.538	0.581	0.565	**0.864**

***Note:** Effort expectancy (EE), Performance expectancy (PE), Facilitating conditions (FC), Price value (PV), Social influence (SI), Cognitive trust (CT), Emotional trust (ET), Trust_IoT-MP (TIM), Behavioural intention (BI).

The discriminant dependability of the measures was determined by comparing their indicator loadings on their respective constructs to their indicator loadings on other constructs. As shown in Table 2, all indicators loaded at or above the 0.70 cutoff value. Each indicator's loadings on its construct were significantly greater and higher than their loadings on other variables. Also, the discriminant validity of the constructs has been established using the Fornell-Larcker criterion (Table 3): (1) the square root of each construct's AVE is greater than its association with another construct, and (2) each item loads most greatly on its associated construct [89,100]. As presented in Table 3, all values are significantly greater than its related construct, demonstrating that discriminant validity is satisfactory.

Table 3: Fornell-Larcker criterion matrix.

Construct	BI	CT	EE	ET	FC	PE	PV	SI	TIM
BI	**0.857**								
CT	0.617	**0.864**							
EE	0.684	0.673	**0.785**						
ET	0.675	0.620	0.694	**0.797**					
FC	0.571	0.624	0.662	0.600	**0.871**				
PE	0.777	0.674	0.637	0.685	0.630	**0.849**			
PV	0.520	0.588	0.550	0.595	0.494	0.560	**0.850**		
SI	0.627	0.604	0.592	0.689	0.576	0.664	0.572	**0.890**	
TIM	0.764	0.672	0.668	0.731	0.659	0.828	0.592	0.695	**0.820**

***Note:** Effort expectancy (EE), Performance expectancy (PE), Facilitating conditions (FC), Price value (PV), Social influence (SI), Cognitive trust (CT), Emotional trust (ET), Trust_IoT-MP (TIM), Behavioural intention (BI).

5.3 Structural Assessment Model and Hypothesis Testing

The hypothesis testing results are depicted in Figure 5 and described in Tables 4, and 5. The value of R2 shows that the endogenous variables explain moderate to high explanatory power in the model, and the values of Q2 are typically consistent with the values of R2 [97]. The Q2 values for behavioural intention to use IoT mobile payments were the highest of all endogenous factors. Specifically, the research model accounted for some variance in respondents' perceptions of emotional trust (adjusted R2 = 0.383) and trust in IoT_MP (adjusted R2 = 0.610) associated with IoT mobile payment usage behavioural intention. Additionally, the research model captured significant variation in behavioural intention (adjusted R2 = 0.682).

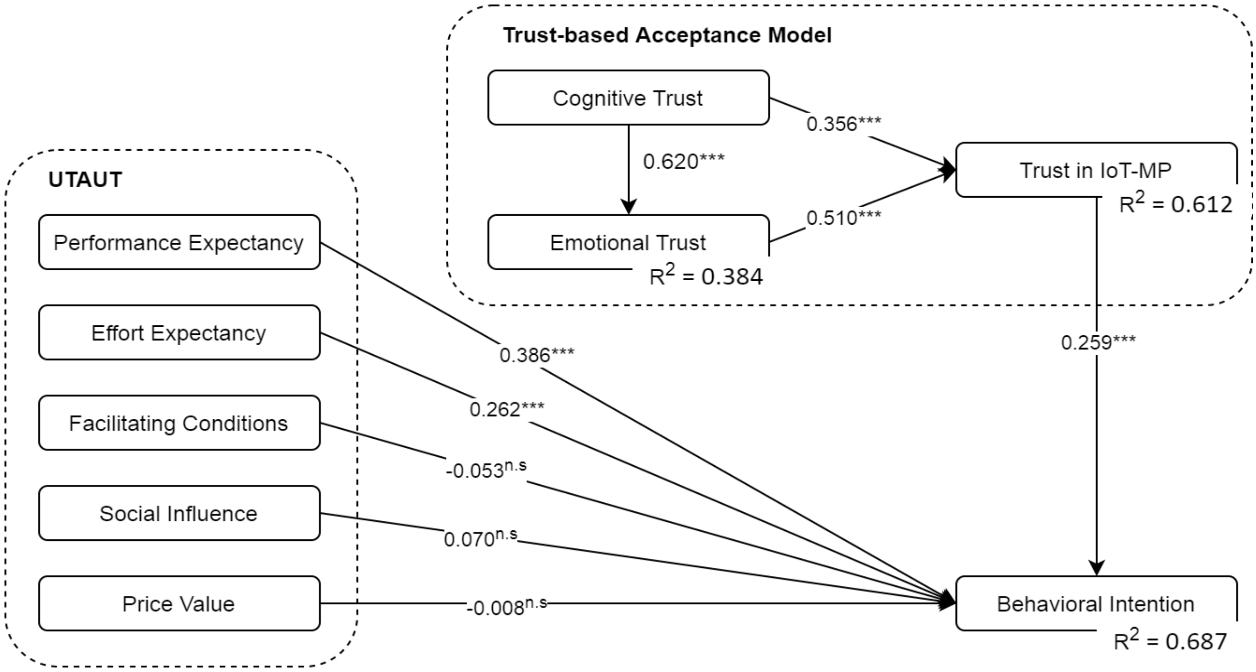

Fig.5: Test results of the structural model. Notes: n.s. = non-significant; *p < 0.05; **p < 0.01; ***p < 0.001.

Table (4). Model Construct PLS Measures.

Endogenous variables	**R^2**	**R^2 Adjusted**	**Q^2**	**Exogenous variables**	**Effect size f^2**
Behavioral intention	0.687	0.682	0.497	Performance Expectancy	0.137
				Effort Expentancy	0.096
				Facilitating Conditions	0.004
				Social Influence	0.007
				Price Value	0.000
				Trust_IoT-MP	0.053
Emotional Trust	0.384	0.383	0.240	Cognitive Trust	0.624
Trust in IoT MP	0.612	0.610	0.408	Emotional Trust	0.413
				Cognitive Trust	0.201

Table 5: PLS structural model results .

Path	**B**	**S.E**	**t value**	**p value**	**f^2**	**VIF**	Supported
PE -> BI	0.386	0.019	6.713	0.000	0.137	3.484	Yes
EE -> BI	0.262	0.020	4.265	0.000	0.096	2.294	Yes
FC -> BI	-0.053	0.018	0.957	0.339	0.004	2.167	No
SI -> BI	0.070	0.018	1.321	0.186	0.007	2.249	No
PV -> BI	-0.008	0.015	0.171	0.864	0.000	1.753	No
CT -> ET	0.620	0.010	19.698	0.000	0.624	1.000	Yes
CT -> TIM	0.356	0.012	9.619	0.000	0.201	1.624	Yes
ET -> TIM	0.510	0.013	13.487	0.000	0.201	1.624	Yes
TIM -> BI	0.259	0.023	3.758	0.000	0.053	4.028	Yes

***Note:** Performance expectancy (PE), Effort expentancy (EE), Facilitating conditions (FC), Price value (PV), Social influence (SI), Cognitive trust (CT), Emotional trust (ET), Trust_IoT-MP (TIM), Behavioural intention (BI).

The result obtained for the path coefficient statistics in Table 5 indicates that the f2 (f values) are consistent with the t values. Moreover, the variance inflation factor (VIF) values are less than 5.0, indicating that the collinearity poses a minimal threat to the results[97]. Hence, the result of the independent hypothesis are further summarise.

Hypothesis 1 was supported, as performance expectancy positively affects users' behavioural intention to use IoT mobile payment ($t = 6.713$, $p < 0.001$). Hypothesis 2 was supported, as the effort expectancy positively affects users' behavioural intention to use IoT mobile payment ($t = 4.265$, $p < 0.001$). Hypothesis 3 was not supported; although the relationship had a negative impact, it was not statistically significant ($t = 0.957$, $p = 0.339$). Also, Hypothesis 4 was not supported. Although the relationship was predicted, the hypothesis between social influence and behavioural intention to use IoT mobile payment was not statistically significant ($t = 1.321$, $p = 0.186$). Likewise, the result obtained did not find evidence to support hypothesis 5, that the price value of IoT mobile payment affected users' behavioural intention to use the system ($t = 0.171$, $p = 0.864$).

Moreover, hypothesis 6 was supported; cognitive trust positively impacts emotional trust in IoT mobile payment ($t = 19.698$, $p < 0.001$). Hypothesis 7 was also supported, as cognitive trust positively influences trust in IoT mobile payment ($t = 9.619$, $p < 0.001$). Likewise, hypothesis 8 was supported, as emotional trust in IoT mobile payment positively impacts trust in IoT mobile payment ($t = 13.487$, $p = < 0.001$). Additionally, the analysis of the study found evidence to support hypothesis 9, that trust positively impacts behavioural intention to use IoT mobile payment ($t = 3.758$, $p < 0.001$).

5.4 PLS Predict

In addition to reporting a model fit, researchers are encouraged to analyse the model using the PLSpredict approach, as Shmueli et al. [101] presented. The PLSpredict is a collection of processes for prediction using PLS path models and the evaluation of their predictive performance. This is due to the rapid and significant development and updates in the PLS-SEM domain [102]. Therefore, the predictive power of the model was determined using the PLSpredict technique [103,104]. Before commencing the PLSpredict technique, it is recommended that the measurement models meet all measurement criteria. Thus, the reflecting measurement models have provided acceptable reliability, convergent validity, and discriminant validity [91,100,104]. Thus, the PLSpredict procedure was launched, and the predictive significance of the model was determined by comparing the mean absolute error (MAE), root mean square error (RMSE), and Q2predict values for the PLS-SEM model against the naive benchmark model (LM). According to the PLSpredict interpretation procedure (Shmueli et al., 2019), the Q2predict is examined initially. The value must surpass the naive benchmark model before RMSE and MAE are assess [103]. Similarly, Due to the non-normal sample (asymmetrically distributed) nature of the data in this investigation, the RMSE and MAE prediction metric was evaluated. Hence, the PLSpredict is run by performing ten (10) k-fold cross-validation. Each fold represents a subgroup of the overall sample, and k is the number of subgroups. According to the analysis, Q2predict < 0, and both RMSE and MAE are all positive. Hence, the proposed model's errors are more significant than those of the linear model. Accordingly, if the PLS-SEM result (compared to the LM) produces lower RMSE (or MAE) prediction errors for none of the indicators, the model lacks predictive power". As a result, the PLS-SEM forecasts do not outperform the LM benchmark. Thus the results demonstrate that the model lacks predictive power, as defined by Shmueli et al. [104]. The PLSpredict result is presented in Table 6.

Table 6: PLSpredict assessment of the original model (PLS) vs. naïve benchmark (LM).

	PLS		**LM**		**PLS-LM**		
	RMSE	**MAE**	**RMSE**	**MAE**	**RMSE**	**MAE**	**Q^2_predict**
BI1	0.811	0.638	0.768	0.587	0.043	0.051	-0.058
BI2	0.772	0.586	0.748	0.561	0.024	0.025	-0.032
BI3	0.838	0.678	0.805	0.646	0.033	0.033	-0.041
ET1	0.923	0.765	0.800	0.646	0.123	0.120	-0.184
ET2	0.953	0.770	0.833	0.637	0.121	0.133	-0.183
ET3	1.036	0.825	0.867	0.662	0.169	0.163	-0.231
CT1	0.982	0.810	0.766	0.605	0.216	0.205	-0.266
CT2	1.067	0.863	0.803	0.628	0.264	0.235	-0.316
CT3	0.968	0.775	0.803	0.641	0.165	0.134	-0.237
CT4	0.861	0.684	0.736	0.589	0.125	0.095	-0.169

6. Discussion

The explosive rise of e-commerce has provided more potential for eCommerce transactions. This is powered by the unabated growth of mobile-based technologies, including the recent surge in mobile payment systems and integrated IoT devices contributing to the surge of Industry 4.0 era. However, these development induces trust concerns [24] and other factors that could challenge the successful adoption of such systems. For example, prior empirical research indicates that consumers are wary about trusting mobile payment with their personal and financial information for mobile transactions [24,28,38]. In contrast, other studies [37,38,38,105,106] indicate concerns about other factors, such as system usefulness, ease of using, the cost associated with the systems, facilitating environment, etc. Despite these concerns, Chin et al. [24] highlighted that mobile payment popularity had increased globally due to the advancement of many technological solutions, such as the integration of NFC in IoT architecture [33]. Thus, with expanding global popularity of IoT and mobile payment, consumers may regard using mobile payment systems as one of the activities that might engage them in using their mobile devices. Furthermore, Users rely on third-party companies to intermediary retailers and service providers and their banks or credit card issuers. Therefore, perceptions of the trust and benefit associated with these systems may influence their adoption significantly.

This study determined the effect of effort expectancy, performance expectancy, facilitating condition, price value, social influence, and perceived trust on behavioural intentions to embrace IoT mobile payment solutions. The study model integrates UTAUT and the trust-based acceptance model, which incorporates two antecedents such as cognitive trust and emotional trust. The study discovered a significant relationship between performance expectancy and behavioural intention, and effort expectancy and behavioural intention. As consumers perceived ease of use and usefulness, their willingness to adopt mobile payment methods increased. However, the finding provides insufficient statistical evidence to support the relationship between facilitating condition and behavioural intention, social influence and behavioural intention, and price value and behavioural intention. Furthermore, the relationship between cognitive trust and emotional trust was positive and significant.

In addition, the outcome of this study showed a positive and significant relationship between cognitive trust and trust in IoT-MP and emotional trust in IoT-MP within the trust-based acceptance model. As consumers' perceived cognitive and emotional trust improved, their general trust in the IoT mobile payment systems also increased. These associations were suggested and substantiated. Another prediction supported by these findings was a strong positive relationship between trust in IoT-MP and behavioural intention to use. Thus, consumers' trust in IoT mobile payment systems improved with their intention to utilise them. In general, there is a highly significant relationship between trust and behavioural intention and between performance expectancy and effort expectancy with behavioural intention to utilise IoT mobile payment ($p < 0.001$). However, when price, social influence, and facilitating conditions were measured, the hypotheses are rejected ($p > 0.5$).

Remarkably, the findings of the study revealed support for current literature as well as conflicts with existing. Firstly, Mun et al. [23] study the factors influencing consumers' intentions to use mobile payment services in Malaysia, particularly millennials. The data indicate that perceived usefulness (seen as performance expectancy), ease of use (seen as effort expectancy), and social influence considerably affect consumers' behavioural intention to utilise mobile payment services. Perceived usefulness is the most important determinant. According to Liébana-Cabanillas et al.[106], perceived usefulness and perceived trust affect the intention to utilise mobile payment services in India. Moreover, Lin et al.[13] identified a significant relationship of effort expectancy, performance expectancy, social influence, price value and facilitating conditions on behavioural intention, indicating consumer intention to use mobile payment. However, this study's findings support existing work regarding the positive effect of performance expectancy and effort expectancy on consumers' behavioural intention [13,23,56,106]. Furthermore, this study does not support existing studies regarding the positive effect of social influence [13,23,56], facilitating conditions, and price value [13,56]. However, the cost of IoT in banking services was found in earlier research as having no effect [55], which supports the outcomes of this study.

Moreover, these findings could be significantly different in different countries because not all nations have a high percentage of mobile payment adoption, and some countries have significant development potential. For example, Russia is one of the important markets for contactless transactions via smartphone wallets; yet, smartphone payments still account for a far smaller share of total payments than traditional cards [108]. Poland's payment card market is critical, considering its current status as Central Europe's largest country. With the emergence of novel payment potentials, traditional payment methods, particularly cash, retain a prominent position [107]. Also, the insignificant hypothesis findings could be due to the nature of the participants. For example, most respondents were university students, who by definition have a greater level of education than the average population. Second, the individuals were relatively young, averaging little more than 22 years. The majority of them are "digital natives," at ease with the use of technology to enhance a variety of their activities. Younger respondents' attitudes regarding financial transactions may be different from those of older ones. Still, consumers believe that using the technology will help them save time, improve efficiency, and increase convenience concerning performance expectancy and effort expectancy. Operating the technology will be effortless and time-consuming [11], As a result, consumer behavioural intention to use will increase as mobile payment services become more advantageous [13.56].

Additionally, this study showed significant correlations between trust and behavioural intention, supporting existing research [24,28,37,38,56,106]. Specifically, Guo and Waechter [37] investigated trust through valence framework and TAM, and the result identified a relationship between initial trust and perceived reward. Furthermore, Park et al. [38] integrate the concepts of trust and intention, and the outcomes were statistically significant. Interestingly, the integration of a trust-based acceptance model by Leong et al. [28] is the only study on mobile payment adoption that utilised a trust-based acceptance model with cognitive and emotional characteristics to examine the trust associated with mobile commerce with a particular emphasis on payment, revealing significant relationship among the corresponding constructs. Also, this study has shown the positive impact of cognitive and emotional trust within the trust-based acceptance model. Research utilising the trust-based paradigm or any other dominant adoption model is absent by focusing exclusively on IoT mobile payment. While several studies have examined trust as a factor in mobile payment uptake [24,38,56,106], each framework relied on a separate collection of theories, base models, and antecedents, as the majority of works focused exclusively on the topic of trust as a single dimension.

6.1 Theoretical Implications

This research contributes by utilising and integrating the UTAUT and trust-based acceptance model to investigate the factors that effect the adoption of IoT mobile payment systems. This is a novel theoretical approach in mobile payment context, as much prior work has concentrated on TAM, UTAUT, and UTAUT2 [35,56]. Similarly, another theoretical contribution is using a trust-based acceptance model to the research on IoT mobile payments, which is only adopted by Leong et al. [28] in the mobile commerce context. This is a significant contribution with substantial implications. Because customers rely on institutions and value their convenience, the substantial determinants are trust, ease of use, and usefulness.

Specifically, this is the first empirical study to examine IoT mobile payment adoption despite Li and Li's [12] study investigating user satisfaction of third-party mobile payment related to the IoT environment. Primarily, previous studies focus on mobile payment [24,31,35,37,41,56,109]. Most of these studies were conducted in various countries, where differences in culture, infrastructure, legalisations, and economics may affect how individuals make decisions. Thus, the relevance of measuring theories and models in varied contexts is emphasised in theory development research [52]. This study's findings contribute to this effort.

Secondly, this study demonstrates the critical importance of effort expectancy and performance expectancy, and as a result, greater attention should be paid to boosting the customer's sense of usefulness [40]. In this case, promotional and marketing efforts should be made to cognitively portray mobile Internet as a more beneficial productive technology that saves time and effort in the customer's mind. Simultaneously with these efforts, practitioners should increase the breadth of services offered by IoT mobile Internet while also ensuring the quality, reliability, and sustainability of their performance, hence increasing customers' perceived usefulness of IoT mobile Internet services [40,110–112] such as transaction, access, and ticketing.

More importantly, customer trust has elicited an interest on the part of Saudi customers, either in terms of their judgement of utility or in terms of determining their proclivity to adopt mobile Internet [40]. As a result, the two primary characteristics of consumer trust in IoT mobile payment, cognitive and emotional, should be strengthened to increase this trust. For example, mobile Internet services should be well-designed to ensure more reliability and high-quality services. These applications should be adequately protected and secured to preserve the user's information. Also, organisations should exercise caution when making promises to their clients concerning mobile Internet-enabled services. This will help clients develop a greater positive thought for these firms' integrity and, as a result, a greater level of trust in their mobile Internet solutions. Additionally, these firms must reassure their clients that any information provided and privacy will be maintained and not shared with any other parties. This, in turn, increases the customer's cognitive and emotional sense of benefic and, thus, the customer's level of trust.

6.2 Practical and Managerial Implications

The outcome of this investigation have consequences for all stakeholders involved in IoT mobile payment systems. Consumers and merchants benefit from the growing popularity of IoT devices, mobile devices, and the increased alternatives for mobile payment systems. Consumers can transfer funds or make purchases without using cash, owning a physical credit card, or visiting a bank from the consumer's perspective. They don't even need a smartphone anymore, as many mobile payment services are now accessible on smartwatches, bracelets, and smart rings. Vendors may enhance sales by responding to consumers' desire for convenience while achieving ease of use and usefulness. Offering IoT mobile payment options may attract consumers who would otherwise avoid purchasing due to a lack of cash. Consumer impulse purchases may result in increased income for vendors.

Vendors of mobile payment systems can also be encouraged to ensure that clients trust these systems and do not view them as excessively hazardous [24]. Hence, trust is highly fragile and any security or privacy breach in a mobile payment system can significantly erode and drive consumers to potential mobile payment technologies and platforms . Therefore a substantial violation of one IoT mobile payment device or system could imperil all other mobile payment systems by eroding consumer trust in all such designs, not just the one that was compromised. As the previous study has [24,28], mobile device users generally trust the platforms that offer them services and goods, but if this trust is eroded, it may expose the relationship customers have with their suppliers.

7. Conclusion

7.1 Limitation and Future Directions

This study has some limitations. First, the respondents who participated in this study belonged to a specific country (Saudi Arabia), where consumers have a broader range of payment choices. Second, the findings of this study may be significantly different in countries with different financial system configurations. Third, this study used only two items to assess the social influence construct. This may introduce some limitations to the research findings, particularly their reliability and validity [94]. However, we discovered that the two-item scales were generally reliable and valid in all circumstances. Future study directions should include overcoming the constraints imposed by a homogeneous population and geographic location. Still, prioritising scales with enough items is encouraged [113]. Hence, further research may examine the possibility of strengthening the social influence construct with more appropriate items.

Additionally, age has been identified as a moderator in several literature studies [52,114]. This implied that age could potentially mitigate severe effects. However, this study does not provide a comparison between different age groups because this was beyond the scope of this study. As a result, future studies can focus on the well-documented moderating influence of age. Finally, our findings may be apply to circumstances other than IoT mobile payment, such as IoT solutions. However, the data was insufficient to establish this assertion. As a result, additional research should be undertaken to understand whether age is a moderator of considerable impact and whether technology adoption factors such as risk perceptions and privacy concerns affect the consumers' behavioural intention of IoT mobile payment. Also, it is critical to conduct similar studies with respondents from other age groups to ascertain whether different outcomes prevail.

Finally, this study used additional rigour measurement to predict the model which is PLSpredict algorithm. However, the findings of its analsysis showed that there is lack of predictive power. Future studies could be conducted to test and predict the models' variables using machine learning tools such as artificial neural network (ANN) and Deep Neural Networks (DNNs). These techniques has been recently suggested to be accessed in technology adoption recearch [115].

7.2 Conclusion Remark

This study determines the effect of adoption factors on customer intention to embrace IoT mobile payment systems through the lens of UTAUT and the trust-based acceptance model. The study adopts theoretical models that determined the factors influencing customer acceptance of IoT mobile payment systems. The results reveal that effort expectancy, performance expectancy, and trust are the most influential dimensions. This study also shows that cognitive trust and emotional trust have a robust relationship to trust. Eventually, this study provides theoretical contributions and empirical insights for both mobile payment and IoT adoption research.

8. References

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Appendix A: The study's Items

Construct	Code	Items	Ref
Performance Expectancy	PE1	I think that using IoT mobile payment allows me to complete financial transactions more quickly.	[49] [13]
	PE2	I think that using IoT mobile payment can save the payment time and allow me to focus on other things.	
	PE3	I think that using IoT mobile payment can increase the convenience of consumption.	
	PE4	I think that using IoT mobile payment would enable me to conduct tasks more quickly	
Effort Expectancy	EE1	I think that IoT mobile payment is easy to use.	[49] [13]
	EE2	I think that using IoT mobile payment is clear and easy to understand.	
	EE3	My interaction with IoT mobile payment would be clear and understandable.	
	EE4	I can easily use IoT mobile payment to consume.	
Facilitating Conditions	FC1	I have the resources that I need to use the IoT mobile payment. (ex: mobile device, credit card, IoT supporting tech)	[49] [13]
	FC2	IoT mobile payment is compatible with other systems that I have used.	
	FC3	I think that IoT mobile payment can be matched with other technologies I use; (ex: easy card, mobile payment)	
Social Influence	SI1	I believe that using IoT mobile payment can improve my social status.	[13]
	SI2	I think people who use IoT mobile payment have higher reputation than those who do not use IoT mobile payment.	
Price Value	PV1	Compared with the normal payment (cash, credit card, mobile payment), I think the price paid for using IoT mobile payment is reasonable.	[52] [13]
	PV2	To me, using IoT mobile payment to pay for online shopping is worth more than it costs. (Ex: reward point)	
	PV3	Compared with the normal payment (cash, credit card, mobile payment), IoT mobile payment provides a good economic value in terms of current market prices.	
Cognitive Trust	CT1	IoT mobile payment always provides accurate financial services.	[28] [39]
	CT2	IoT mobile payment always provides reliable financial services.	
	CT3	IoT mobile payment always provides safe financial services.	
Emotional Trust	ET1	I feel secure using IoT mobile payment for my payment.	[28] [39]
	ET2	I feel comfortable using IoT mobile payment for my payment.	
	ET3	I feel content using IoT mobile payment for my payment.	
Trust_IoT-MP	TIM1	IoT mobile payment systems are trustworthy.	[24]
	TIM2	IoT mobile payment systems have my best interest in mind.	
	TIM3	IoT mobile payment systems have high integrity.	
	TIM4	Generally speaking, I have confidence in the IoT mobile payment platforms.	[28]
Behavioural Intention	BI1	I am likely to make a retail purchase or send money to others with an IoT mobile payment system.	[49] [24]
	BI2	In my daily life, I will continue to use IoT mobile payment	[13]
	BI3	I am willing to bind my credit card or financial account to IoT mobile payment.	