



Understanding the Factors Influencing Consumer Adoption of Wearable Payment Devices

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Abstract

The rapid digitalization of financial services has accelerated the adoption of mobile and contactless payments, yet payment-only wearables (NFC-enabled wristbands, rings, and tags designed exclusively for payments) remain a niche segment with limited consumer uptake. This dissertation investigates the factors influencing consumers' behavioral intention (BI) to adopt payment-only wearables by extending the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2). The model integrates trust, compatibility, and perceived aesthetics as additional constructs and examines the moderating role of personal innovativeness.

Data was collected through a structured online survey (N = 254) and analyzed using multiple linear regression and moderation analysis. The model explained 70.6% of the variance in BI, demonstrating strong predictive power. Results show that compatibility was the strongest determinant of BI, followed by aesthetics, performance expectancy, and price value. Social influence and facilitating conditions had weaker but significant effects, while effort expectancy and trust were not significant predictors, suggesting that ease of use and security are now baseline expectations rather than differentiators. Moderation analysis revealed that innovativeness amplifies the effects of performance expectancy, compatibility, trust, and social influence on BI.

The study makes two key contributions. Theoretically, it adapts UTAUT2 to an emerging payment context, showing that adoption drivers evolve with market maturity. Practically, it provides guidance for firms to emphasize usefulness, lifestyle fit, design appeal, and innovative consumer segments in order to accelerate acceptance of payment-only wearables.

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Keywords: Payment-only wearables, Wearable payment devices, Contactless payments, Technology adoption, UTAUT2, Behavioral intention, Trust, Compatibility, Perceived aesthetics, Innovativeness.

Sumário

A rápida digitalização dos serviços financeiros acelerou a adoção de pagamentos móveis e contactless. No entanto, os wearables de pagamento (pulseiras, anéis e tags com tecnologia NFC, concebidos para efetuar unicamente pagamentos) permanecem um segmento de nicho. Esta dissertação investiga os fatores que influenciam a intenção comportamental (BI) de adoção destes dispositivos, através da extensão do modelo UTAUT2 incorporando as variáveis confiança, compatibilidade e estética percebida, bem como o papel moderador da inovação pessoal.

Os dados foram recolhidos através de um questionário online (N = 254) e analisados com recurso a regressão linear múltipla e análise de moderação. O modelo explicou 70,6% da variância em BI, demonstrando elevado poder preditivo. Os resultados revelam que a compatibilidade foi o determinante mais forte, seguida da estética, expectativa de desempenho e valor de preço. A influência social e as condições facilitadoras tiveram efeitos mais fracos embora significativos, enquanto a expectativa de esforço e a confiança não foram fatores significativos, sugerindo que a estes são agora expectativas garantidas e não fatores diferenciadores. A análise de moderação mostrou que a inovação amplifica os efeitos da expectativa de desempenho, compatibilidade, confiança e influência social sobre a intenção de adotar.

O estudo traz duas contribuições principais. Teoricamente, adapta o UTAUT2 a um contexto emergente de pagamentos, mostrando que os determinantes da adoção evoluem com a maturidade do mercado. Praticamente, fornece orientações para que as empresas valorizem a utilidade, integração no estilo de vida, apelo estético e consumidores inovadores, de modo a acelerar a adoção destes dispositivos.

Título: Compreender os Fatores que Influenciam a Adoção de Dispositivos de Pagamento Wearable pelos Consumidores

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Palavras-chave: Wearables exclusivamente de pagamento, Dispositivos de pagamento wearable, Pagamentos contactless, Adoção tecnológica, UTAUT2, Intenção comportamental, Confiança, Compatibilidade, Estética percebida, Inovação.

Table of Contents

1. Introduction	1
2. Literature Review	2
2.1. Evolution of payments	2
2.2. Theoretical Background	4
Technology Acceptance Model.....	4
Diffusion of Innovations	4
Unified Theory of Acceptance and Use of Technology.....	4
Unified Theory of Acceptance and Use of Technology 2.....	5
UTAUT2 applied to this research	6
2.3. Hypotheses development.....	8
2.3.1. Performance Expectancy (PE)	8
2.3.2. Effort Expectancy (EE)	9
2.3.3. Social Influence (SI).....	10
2.3.4. Facilitating Conditions (FC).....	11
2.3.5. Price Value (PV)	11
2.3.6. Trust (TR).....	12
2.3.7. Compatibility (CM).....	13
2.3.8. Perceived Aesthetics (PA).....	14
2.3.9. Innovativeness (IN).....	16
2.3.9.1. Innovativeness and Performance Expectancy	17
2.3.9.2. Innovativeness and Effort Expectancy	17
2.3.9.3. Innovativeness and Compatibility	18
2.3.9.4. Innovativeness and Facilitating Conditions	19
2.3.9.5. Innovativeness and Trust.....	20
2.3.9.6. Innovativeness and Social Influence	20
2.4. Conceptual Model	21
3. Methodology	22
3.1. Design.....	22
3.2. Participants and sampling.....	22
3.3. Instrument Development	23
3.4. Data Cleaning and Screening	24
3.5. Data Analysis Methodology.....	24
3.5.1 Descriptive Statistics	25
3.5.2 Reliability Testing.....	25
3.5.3 Normality Assessment.....	25
3.5.5 Correlation Analysis.....	26
3.5.6 Multiple Linear Regression (MLR).....	26

3.5.7. Moderation Analysis	27
4. Results and Discussion.....	28
4.1. Descriptive Statistics	28
4.2. Reliability Analysis	29
4.3. Assessment of Normality	29
4.4. Correlation Analysis.....	30
4.5. Multiple Linear Regression Analysis.....	31
4.5.1. Multiple Linear Regression Results	31
4.5.2. Discussion of MLR's Results.....	33
4.6. Moderation Analysis	36
4.6.1. Moderation Results	36
4.6.1.1. Moderation of IN on the relationship between PE and BI	36
4.6.1.2. Moderation of IN on the relationship between EE and BI.....	37
4.6.1.3. Moderation of IN on the relationship between CM and BI.....	37
4.6.1.4. Moderation of IN on the relationship between FC and BI.....	38
4.6.1.5. Moderation of IN on the relationship between TR and BI.....	39
4.6.1.6. Moderation of IN on the relationship between SI and BI	39
4.6.2. Discussion Moderation.....	40
5. Conclusion.....	43
References	45
Appendices	47
Appendix 1: Questionnaire.....	47
Appendix 2: Instrument Development	57
Appendix 3: Mahalanobis distance	58
Appendix 4: Descriptive Statistics	58
Appendix 5: Reliability Analysis - Cronbach's Alpha.....	61
Appendix 6: Normality Assessment.....	64
Appendix 7: Correlation Analysis.....	65
Appendix 8: Multiple Linear Regression Analysis.....	65
Appendix 9: Moderator Analysis	70

List of Abbreviations

Behavioral Intention (BI)

Compatibility (CM)

Diffusion of Innovations (DOI)

Effort Expectancy (EE)

Facilitation Conditions (FC)

Innovativeness (IN)

Near Field Communication (NFC)

Perceived Aesthetics (PA)

Performance Expectancy (PE)

Price Value (PV)

Radio Frequency Identification (RFID)

Social Influence (SI)

Theory of Acceptance (TAM)

Trust (TR)

Unified Theory of Acceptance and Use of Technology (UTAUT)

Unified Theory of Acceptance and Use of Technology 2 (UTAUT2)

Wearable Payment Devices (WPD)

1. Introduction

Digitalization has transformed financial services, with contactless and mobile payments becoming widely adopted (Sahi et al., 2021; Al-Okaily, 2020), particularly after the COVID-19 pandemic heightened consumer demand for speed, convenience, and security (Sleiman et al., 2023). Among the innovations in this space, wearable payment devices have emerged as a promising solution, enabling fast, secure, and hands-free transactions (Slade et al., 2015; Tan et al., 2014). Within this category, payment-only wearables (such as NFC-enabled wristbands, rings, and tags) are designed exclusively for payments, in contrast to multifunctional wearables like smartwatches (Liébana-Cabanillas et al., 2014; Gerpott & Meinert, 2017). Despite their technological readiness and potential advantages, these devices remain a niche segment, overshadowed by multifunctional wearables and facing limited consumer uptake (Grand View Research, 2024; Mordor Intelligence, 2025).

This mismatch between potential and adoption highlights an important gap. While prior research on digital and mobile payments has emphasized drivers such as usefulness, ease of use, and trust (Venkatesh et al., 2012; Oliveira et al., 2016; Patil et al., 2020), payment-only wearables remain underexplored. Their dual nature, as functional payment tools and visible fashion accessories, suggests that factors like aesthetics and lifestyle compatibility may be equally decisive in shaping consumer behavior (Chuah et al., 2016; Lee et al., 2020). Without considering these unique influences, both academic research and industry practice risk overlooking what motivates or discourages adoption of this emerging technology.

To address this gap, this dissertation applies and extends the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) (Venkatesh et al., 2012) to investigate adoption of payment-only wearables. Alongside the core UTAUT2 constructs, the study incorporates trust, compatibility, and perceived aesthetics, while also testing the moderating role of personal innovativeness. By focusing on BI at the pre-adoption stage, the research captures early consumer attitudes that are particularly relevant for a technology still in the early stages of market diffusion.

2. Literature Review

2.1. Evolution of payments

Digital payments, a broad term encompassing any financial transaction made through digital means (Song et al., 2023), have rapidly expanded due to e-banking and digital payment systems growth (Sahi et al., 2021), especially during the COVID-19 pandemic (Sleiman et al., 2023), becoming pervasive worldwide (Al-Okaily, 2020). A key subset of digital payments is mobile payments, which refer to any payment made via mobile devices like cards, phones, smartwatches or other wireless-enabled gadget (Song et al., 2023; Spinelli et al., 2024; Oliveira et al., 2016; Chaveesuk et al., 2021), usually via technologies like Near-Field Communication (NFC), Bluetooth, Radio Frequency Identification (RFID), Wi-Fi, etc (Dahlberg et al., 2008; Dewan & Chen, 2005). These are often classified as remote when payer and payee are apart (eg. online shopping) (Luna et al., 2019) or proximity-based when payer and payee are physically close, which involve scanning, tapping, or swiping with a mobile device (Slade et al., 2013; Jain et al., 2023; Luna et al., 2019).

NFC, which allows secure, short-range communication between an enabled device and a compatible terminal (Slade et al., 2015) has further advanced proximity payments by enabling contactless transactions (de Luna et al., 2019; Mallat, 2007; Ondrus & Pigneur, 2009). With a range of only a few centimeters, it ensures payment data is transferred only to the intended recipient (Nezhad et al., 2024). Contactless payments gained traction during COVID-19 due to health concerns and increased demand for convenience (Ismail et al., 2022). These involve tapping an NFC enabled device near a reader without inserting or swiping a card (Nezhad et al., 2024).

Wearable payments are a type of contactless payment using NFC-enabled wearable devices (Tan et al., 2014; Gerpott & Meinert, 2017) that allow consumers to pay anytime, anywhere through smartwatches, rings, wristbands, keychains, or RFID tags (Liébana et al., 2014; Bezhovski, 2016). These devices are typically small, portable and integrated into accessories, gadgets, clothing or even microchips and smart tattoos (Luczak et al., 2020; Seneviratne et al., 2017).

This study focuses on payment-only wearables: devices designed solely for secure, seamless payments using NFC, such as smart rings, bracelets, and wristbands (Tan et al., 2014; Gerpott &

Meinert, 2017). Unlike multifunctional wearables (such as smartwatches or fitness trackers) which serve multiple purposes including communication, health tracking, and entertainment, payment-only wearables are optimized for payments alone (Liébana-Cabanillas et al., 2014) and work like contactless cards, offering quick, hands-free transactions by tapping the device at a POS terminal (Bezhovski, 2016). Although they have the potential to become the next generation of payment devices, their market share remains small (Lee et al., 2020; Najdawi et al., 2019). Recent industry reports show that smartwatches and fitness trackers together account for around 94% of the wearable payments market, leaving only about 6% for payment-only devices such as rings and wristbands (Grand View Research, 2024; Mordor Intelligence, 2025; GMI Insights, 2024) (See figure 1). This is why research on payment-only wearables is needed, to understand the factors that may drive or hinder their adoption and help realize their potential in the evolving payment landscape.

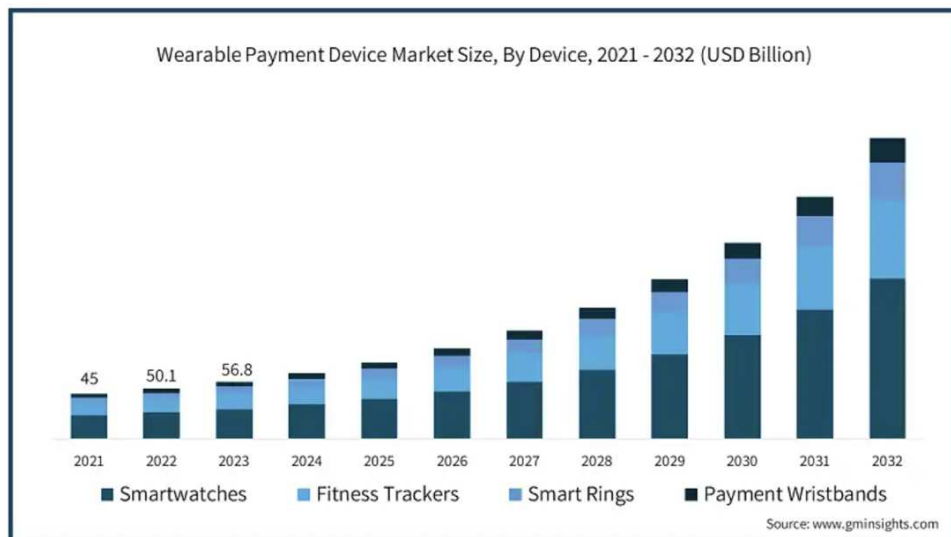


Figure 1: Market Size Forecast of Wearable Payment Devices, by Device

2.2. Theoretical Background

Technology Acceptance Model

A wide range of theories have been developed to understand the factors that influence the adoption and diffusion of new technologies. One of the most influential is the Technology Acceptance Model (TAM) proposed by Davis (1989) (King & He, 2006; Luna et al., 2019), which introduced the constructs of Perceived Usefulness (PU) and Perceived Ease of Use (PEOU). While TAM has been widely applied to study the acceptance and use of technologies, its focus is primarily on

organizational contexts and it adopts a deterministic approach that largely overlooks personal differences in users's characteristics, assuming that technology use is always voluntary although it is frequently applied in mandatory use contexts, such as workplace settings where employees are required to use certain systems. (Agarwal & Prasad, 1999; Slade et al., 2015; Patil et al., 2020). As a result, modified and extended versions have been introduced to address these limitations and accommodate emerging technologies (Kuan & Chau, 2001; Agarwal & Prasad, 1998, Sleiman et al., 2023).

Diffusion of Innovations

Another influential framework in technology adoption research is Rogers' Diffusion of Innovations theory (DOI) (Rogers, 1995; 2003), which explains how innovations spread through communication channels over time, emphasizing attributes such as relative advantage, compatibility, complexity, trialability, observability, and personal innovativeness (Rogers, 2003; Greenhalgh et al., 2004). It has been widely applied in information systems to predict consumer adoption (Oliveira & Martins, 2011; Slade et al., 2015). Nevertheless, DOI has been criticized for its "pro-innovation bias," its reliance on a linear, stage-based view of adoption, and its limited attention to individual-level psychological and contextual factors (Rogers et al., 2014). While valuable for understanding broad diffusion patterns, DOI is less suited to capturing the nuanced drivers of adoption in emerging technologies.

Unified Theory of Acceptance and Use of Technology

Recognizing the limitations of individual models, Venkatesh et al. (2003) proposed the Unified Theory of Acceptance and Use of Technology (UTAUT), which integrates eight prominent pre-existing models of technology adoption, including TAM, DOI and others to explain employee adoption within organizational settings where technology use is often mandatory (Slade et al., 2015). The model identifies four key predictors of users' behavioral intention and usage: performance expectancy, effort expectancy, social influence, and facilitating conditions, with effects moderated by gender, age, experience, and voluntariness of use (Venkatesh et al., 2003).

UTAUT explains approximately 70% of the variance in usage intention and about 50% of the variance in actual technology use, outperforming the individual theories it unified (Venkatesh et

al., 2003; Tang & Tsai, 2024) and becoming one of the most widely adopted models for investigating technology acceptance in various domains, including mobile payments, NFC-based payments, e-wallets, and wearable payment devices (Tang & Tsai, 2024; Rabaa'i & Zhu, 2021).

However, its focus on organizational settings, where technology adoption is often mandatory, limits its suitability for voluntary, consumer-driven technologies and although voluntariness of use is included as a moderating variable, the model does not fully account for purely voluntary adoption scenarios that are typical in consumer contexts (Venkatesh et al., 2003; Slade et al., 2015). This limits its applicability to consumer-focused technologies, which often involve additional factors such as trust, perceived security, privacy concerns, lifestyle compatibility, hedonic motivation, and personal innovativeness, all of which play significant roles in individual decision-making (Islam et al., 2024; Slade et al., 2015). To address these gaps, researchers have extended UTAUT with additional variables relevant to consumer contexts (Al-Saedi et al., 2020; Dwivedi et al., 2019).

Unified Theory of Acceptance and Use of Technology 2

Building on the UTAUT, Venkatesh et al., (2012) developed the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) to address the limitations of the original model when in consumer-focused settings. The UTAUT2 retains the core constructs of the UTAUT and extends it by adding hedonic motivation, price value, and habit (recognizing that consumer adoption is typically voluntary and influenced by individual lifestyle factors) to better explain consumer acceptance behavior. It also modifies the original model by adding a direct path from facilitating conditions to behavioral intention, acknowledging that perceived available support can directly shape intention to adopt a technology in a consumer setting, and removing voluntariness of use as a moderator, since consumer technology use is typically discretionary, leaving no meaningful variation of voluntariness in the relationship between social influence and behavioral intention to adopt (Venkatesh et al., 2003, 2012).

The UTAUT2 demonstrated stronger explanatory power compared to earlier models, explaining 74% of the variance in behavioral intention, (compared to 56% of the original UTAUT) (Venkatesh et al., 2012). It has been successfully applied in diverse contexts such as mobile banking (Bhatiasevi, 2016), mobile payments (Khalilzadeh et al., 2017) and digital shopping

(Yang et al., 2021). Researchers have further extended the UTAUT2 by adding context-specific constructs like trust, privacy, aesthetics and compatibility, demonstrating its flexibility and relevance for emerging technologies (Al-Okaily et al., 2020; Oliveira et al., 2016; Kranthi & Ahmed, 2018).

Given that this research focuses specifically on consumer perceptions of wearable payment devices, whose use is entirely voluntary and discretionary, the UTAUT2 offers a robust and appropriate theoretical foundation for understanding consumer behavior in such a context. However, some adaptations are necessary since not all original UTAUT2 constructs are suitable for the specific context of payment-only wearables.

UTAUT2 applied to this research

First, this study focuses exclusively on Behavioral Intention (BI) rather than actual usage behavior. BI refers to “a person’s subjective probability that they will perform the behavior in question” (Fishbein & Ajzen, 1975) and is widely recognized as the most immediate motivational driver of technology adoption. Technology adoption can be viewed as occurring in two phases: (1) a pre-adoption phase, where individuals form intentions based on perceptions and attitudes toward the innovation, and (2) a post-adoption phase, where actual usage takes place (Rogers, 2003; Venkatesh et al., 2012). In contexts where technologies are still in the early stage of market diffusion, researchers have often focused on BI rather than actual use, given the limited adoption levels and the fact that most consumers have not yet engaged with the technology in practice (Liébana-Cabanillasa et al., 2017; Ooi & Tan, 2016; Kim et al., 2010). It has been consistently identified as one of the best predictors of actual use (Venkatesh & Davis, 2000; Sheppard et al., 1988, Zhang et al., 2012), and it represents a central construct in TAM, UTAUT and UTAUT2. This reasoning applies equally to payment-only wearable devices, which remain at an early stage of diffusion with limited market penetration. Actual usage among the general population is still low and confined largely to early adopters, whose characteristics may not represent later adopters, and most respondents would report no usage at all. Such conditions would lead to highly unbalanced data that is unsuitable for robust statistical analysis. Measuring BI instead allows the inclusion of both users and non-users, enabling the identification of factors influencing potential

adoption at the pre-adoption stage and providing valuable insights for forecasting future uptake of emerging payment technologies.

Second and accordingly, habit, defined as the extent to which people tend to perform behaviors automatically due to prior learning (Venkatesh et al., 2012), is more relevant to study continued use rather than initial intention to adopt since users have no prior experience using the technology (Al-Okaily et al., 2020; Oliveira et al., 2016). Since payment-only wearables are still in an early adoption phase, the automaticity implied by habit is theoretically unjustifiable at this stage.

Third, hedonic motivation, defined as the fun or pleasure derived from using a technology (Venkatesh et al., 2012), is also considered irrelevant here, since payment-only wearables are purely utilitarian devices designed for secure, convenient transactions rather than enjoyment or entertainment (Al-Okaily et al., 2020). Therefore, both constructs have been excluded to ensure the model remains aligned with the functional nature of the product and the study's focus on initial adoption intention.

Finally, while the original UTAUT2 model proposes age, gender, and experience as moderators of the relationships between its core constructs and behavioral intention/use behavior (Venkatesh et al., 2012), these will not be included in the present study. This decision is justified because, while the study examines multiple determinants of behavioral intention, another central objective is to test personal innovativeness as a moderator. Excluding the original demographic moderators simplifies the model and allows for a more focused analysis of a construct that is particularly relevant to emerging technologies such as payment-only wearables, where early adoption is often driven by individuals with a greater willingness to experiment with new solutions.

Next section presents the core constructs of the UTAUT2 considered in this study: Performance Expectancy, Effort Expectancy, Facilitating Conditions, Social Influence and Price Value, and introduces three additional constructs tailored to the context of payment-only wearable devices: Trust, Perceived Aesthetics and Compatibility. Furthermore, it includes Personal Innovativeness as a moderating variable of Performance Expectancy, Effort Expectancy, Facilitating Conditions, Compatibility, Trust and Social Influence. Finally, this section outlines the hypotheses derived from these constructs.

2.3. Hypotheses development

2.3.1. Performance Expectancy (PE)

In UTAUT2, PE is redefined for the consumer context as “the degree to which using a technology will provide benefits to consumers in performing certain activities”, which relates to how users view a technology's ability to help them complete a task, be benefic in daily activities, implying benefits like efficiency, speed, and precision (Venkatesh et al., 2003; 2012). This consumer-focused definition captures the idea that the technology is useful and adds value to a consumer's experience.

PE is conceptually similar to Perceived Usefulness (PU) in TAM and overlaps with related constructs such as Relative Advantage (Rogers, 2003), Outcome Expectations (Bandura, 1986) and Mobile Usefulness (Ooi & Tan, 2016).

Numerous studies confirm PE and related constructs to be some of the most significant predictors of behavioral intention to use technology in both mandatory and voluntary settings (Kim et al., 2010; Venkatesh et al. 2012; Alaeddin et al., 2018; Bailey et al., 2017)

This relationship holds particularly true in mobile and digital payment environments, where performance-related benefits, such as speed, efficiency, and convenience, are central to consumer value (Oliveira et al., 2016; Leong et al., 2013; Ooi & Tan, 2016), such as NFC payments (Pal et al., 2015), QR mobile payments (Islam et al., 2024) and remote mobile payments (Al-Okaily et al., 2020), etc (Kim et al., 2010; Pham and Ho, 2015). In wearable payment contexts, PU has also been shown to significantly affect adoption intentions for example, Lee et al. (2020) confirmed that Mobile Usefulness positively influenced intention to use wearable payments among Malaysian users of WPD.

The rationale behind this consistent finding is that users evaluate a technology based on the utilitarian benefits and performance enhancements it offers in completing relevant tasks. For payment-only wearables, performance benefits can be performing payment tasks more effectively or conveniently, simplified transactions and reduced payment time, meaning when consumers believe that the device will enhance their “payment performance,” they are more likely to adopt it. Based on what was stated above, it is hypothesized that:

H1: Performance Expectancy positively influences the Behavioral Intention to use payment-only wearables.

2.3.2. Effort Expectancy (EE)

Building upon the foundational understanding of how users perceive the benefits of a technology (PE), it is also crucial to consider the effort users anticipate needing to invest to use that technology. EE is the degree of ease associated with consumers' use of technology (Venkatesh et al. 2012). In consumer contexts, it captures perceptions about how simple or difficult it is to learn how to use and interact with a technology.

EE is conceptually similar to Perceived Ease of Use (PEOU) from TAM (Davis, 1989) and Mobile Ease of Use (MEOU) from MTAM (Ooi & Tan, 2016), both of which capture the degree to which a person believes that using a particular system or technology would be free of effort.

Numerous studies have identified EE as a significant predictor of intention to adopt mobile payments, contributing to a more precise prediction of adoption intention (Madan & Yadav, 2016; Bankole & Bankole, 2017; Rita et al., 2018). Other findings corroborate the role of EE (or PEOU) as a key factor influencing consumers' use intentions for technologies like QR mobile payments (Islam et al., 2024), smart home technology (Nikou, 2019), and even wearable payment devices (Al Mamun et al., 2023). PEOU and MEOU are considered some of the most influential attributes in technology adoption, with robust support from prior studies (Luna et al., 2019; Pal et al., 2015; Nikou, 2019; Lew et al., 2020; Kim et al., 2010).

Despite some mixed findings, the premise that ease of use is important for the adoption of new technologies remains strong, especially in early adoption stages, as is the case of payment-only wearables which allow for simple and quick transactions with minimal effort. If consumers find the devices intuitive and low-effort, they are more likely to consider adopting them. Therefore it is hypothesized that:

H2: Effort expectancy positively influences behavioral intention to use payment only wearables.

2.3.3. Social Influence (SI)

SI is a core construct in both UTAUT and UTAUT2 and it is defined in the latter as "the extent to which consumers perceive that important others (e.g., family and friends) believe they should use a particular technology". It is theorized to directly influence users' BI to use a system (Venkatesh et al., 2012), building on the earlier concept of Subjective Norm (SN) from the Theory of Reasoned Action (Fishbein & Ajzen, 1975) and the Theory of Planned Behavior (Ajzen, 1991), both of which emphasize the role of normative pressure in shaping behavioral intentions.

Numerous studies in the context of mobile payments, including NFC payments, e-wallets and QR code systems, have consistently found that SI positively impacts BI, (Nysveen et al. 2005; Schierz et al. 2010, Oliveira et al., 2016; Patil et al., 2020; Slade et al., 2015). Some studies even rank SI among the most influential factors (Al-Okaily et al., 2020; Luna et al., 2019). Although its strength may be moderated by variables such as age, gender, and experience, Dwivedi et al., 2019 found SI to significantly influence intention even without any moderating variable. Based on what was previously stated, it is hypothesized that:

H3: Social influence positively influences behavioral intention to use payment only wearables.

2.3.4. Facilitating Conditions (FC)

In UTAUT2, FC refers to "consumers' perceptions of the resources and support available to perform a behavior" (Venkatesh et al., 2012). The rationale is that, in consumer contexts, favorable FC are expected to positively influence BI. Meaning that when consumers perceive that they have the necessary resources, knowledge, and support to use a technology, they are more likely to intend to use it (Venkatesh et al., 2012; Neves et al., 2025).

In the original UTAUT model, FC was hypothesized to have a direct influence on technology use, rather than behavioral intention (Venkatesh et al., 2003). The idea is that in organizational settings, for which UTAUT was initially developed, FC serves as a predictor for actual usage since it is typically mandatory. However, when extending UTAUT to a consumer context in UTAUT2, FC was reconceptualized as a direct determinant of BI, in addition to its existing relationship with actual use (Venkatesh et al., 2012).

According to UTAUT2 and other studies, this relationship is expected to be positive (Venkatesh et al., 2012; Patil et al., 2020; Neves et al., 2025; Tang & Tsai, 2023).

In the case of payment-only wearables, a relatively nascent technology, perceived FC such as payment terminal support and access to technical assistance may play a crucial role in shaping adoption intentions. Therefore, building on the theoretical foundation of UTAUT2 and prior empirical evidence from adjacent contexts, the following hypothesis is proposed:

H4: Facilitating conditions positively influences behavioral intention to use payment only wearables.

2.3.5. Price Value (PV)

The UTAUT2 explicitly incorporates Price Value as a key determinant of behavioral intention. This addition was made because, unlike in organizational settings where the employer typically covers the costs, consumers themselves bear the monetary costs associated with acquiring and using technology (Venkatesh et al., 2012). These costs, such as the price of devices or service fees, can be significant and have been noted as potentially decisive in shaping consumer adoption decisions.

PV is defined as the consumer's cognitive trade-off between the perceived benefits derived from using a technology and the monetary cost incurred for its use (Dodds et al. 1991, Venkatesh et al., 2012). PV is evaluated positively when consumer's perceptions of the benefits of using the technology outweigh its monetary cost, and a positive perception of this cost-benefit trade-off directly and positively influences BI to adopt that technology (Venkatesh et al., 2012).

Studies applying UTAUT2 to various consumer technologies, including digital and mobile payments, have also examined the influence of PV or related constructs on behavioral intention (Tang & Tsai, 2024) and have found positive associations between PV and BI (e.g. mobile payment systems and platforms such as JoMoPay, where cost-efficiency was a key factor in their adoption decisions (Al-Okaily et al., 2020)). Likewise, Perceived Cost, a related concept, has also been

shown to have a negative influence on adoption when consumers view the technology as expensive like smart home technology (Nikou, 2019).

Regardless of some mixed findings, the UTAUT2 recognizes consumers' sensitivity to costs and the perceived value of technology. It is therefore reasonable to expect that the perceived benefits of payment-only wearables relative to their price influence consumers' intent to use them. Hence, it is hypothesized that:

H5: Price value positively influences behavioral intention to use payment only wearables.

2.3.6. Trust (TR)

TR, defined as individuals' willingness, security, and confidence to rely on a system and expect it to prevent failure (Kim et al., 2011), has shown to be a crucial determinant of technology adoption in mobile and electronic payments (Gefen et al., 2003; Patil et al., 2020). In electronic transactions, where risks and uncertainty are high, TR is essential for reducing concerns and enabling adoption (Alrawad et al., 2023), often assessed through perceptions of a provider's ability, integrity, and benevolence (Zhou, 2013). In mobile commerce, TR becomes even more critical due to spatial and temporal separation between buyer and seller and the sensitivity of shared data. It reduces uncertainty, enhances confidence, and fosters positive expectations of provider competence and honesty (Alrawad et al., 2023).

Perceived Security (PS), a related construct defined as consumers' belief in the safety of online payments and protection of financial data (Vijayasathy, 2004), supports trust by ensuring transaction safety, thereby promoting adoption (Khalilzadeh et al., 2017; Oliveira et al., 2016; Liébana-Cabanillas et al., 2017). Conversely, Perceived Risk (PR), defined as the potential for negative outcomes in new payment systems, hinders adoption (Mandrik & Bao, 2005). Evidence shows TR may serve as both a direct determinant of intention and an antecedent to PR, indirectly shaping adoption (Marriott & Williams, 2018; Slade et al., 2013).

Empirical studies confirm PS positively influences intention to use technologies like NFC payments, internet banking and mobile wallets (Cheng et al., 2006; Shin, 2009; Al-Okaily et al.,

2020). TR has been shown to reduce risk perceptions and reinforce provider reliability (Slade et al., 2015; Alrawad et al., 2023). Across mobile wallets, mobile ticketing, and banking, TR directly and positively influenced BI, in some cases even surpassing PU (or EE) (Shin, 2010).

For wearable payment devices, still at an early adoption stage, we expect TR to be especially vital, since it reduces perceived hazards, enhances confidence, and encourages adoption (Al-Mamun et al., 2023). Hence, we hypothesize:

H6: Trust positively influences behavioral intention to use payment-only wearables.

2.3.7. Compatibility (CM)

Lifestyle CM, rooted in Rogers' DOI theory, refers to the degree to which an innovation aligns with an individual's existing values, routines, and needs. In mobile contexts, this concept is often captured as Mobile Perceived Compatibility (MPC), the extent to which a technology integrates with a user's lifestyle and behavioral patterns (Ooi & Tan, 2016; Nikou, 2019). The literature consistently shows that consumers are more likely to adopt technologies that fit seamlessly into their daily lives (Veal, 1993).

In digital and mobile payment research, CM has been widely recognized as a key predictor of adoption intention (Mallat, 2007; Oliveira et al., 2016; Sitorus et al., 2019). Studies show that when payment systems align with consumers' habits and preferences, they are more likely to be accepted (Oliveira et al., 2016, Al Mamun et al., 2023). While some research suggests CM primarily operates indirectly, by influencing constructs such as PU and PEOU (Liébana-Cabanillas et al., 2018; Nikou, 2019), other studies report strong direct effects on BI (Ramos-de-Luna et al., 2016).

Specifically, in the context of wearable payment devices (WPD), CM has emerged as a particularly influential factor. Al Mamun et al. (2023) found that when wearable payment solutions fit with users' lifestyles and routines, the likelihood of adoption significantly increases. Their study reported CM as the strongest predictor of intention to use WPDs, underscoring its importance in voluntary adoption contexts. Similar conclusions were drawn in studies on smartphone credit

cards, where MPC was found to positively influence both intention to use and perceptions of usefulness and ease of use (Ooi & Tan, 2016).

Although a few studies have found weaker or indirect effects in specific payment contexts (e.g., NFC), there is strong support for lifestyle compatibility as a decisive factor, especially when the technology, like payment-only wearables, is worn daily and becomes part of the user's self-image and behavior. Accordingly, we propose:

H7: Compatibility positively influences behavioral intention to use payment only wearables.

2.3.8. Perceived Aesthetics (PA)

While traditional adoption frameworks such as TAM, UTAUT, and UTAUT2 emphasize functionality and usability, the adoption of wearable payment devices often depends on factors beyond utility. One prominent determinant is PA, defined as the extent to which a device is perceived as visually attractive, stylish, and pleasing (Yang & Hsu, 2011).

Because payment-only wearables are worn on the body, they operate simultaneously as technological tools and fashion accessories. Their visibility in daily use means that design elements may influence consumer perceptions as strongly as technical capabilities (Yang et al., 2016; Lee et al., 2020). This blending of fashion and technology, sometimes described as “fashnology” (Chuah et al., 2016), highlights the dual function of these devices: enabling payments while signaling identity, style, and social affiliation.

Fashion Theory reinforces this perspective by framing aesthetic needs as integral to consumer behavior (Lee et al., 2020). PA captures both intrinsic motives, such as enjoyment, beauty, and emotional satisfaction, and extrinsic motives, such as social signaling and perceived prestige (Tzou & Lu, 2009; Kumar & Garg, 2010). Thus, when evaluating wearables, users assess not only performance but also appearance, considering what the device communicates about them (Rauschnabel et al., 2016).

A critical component of PA is Visual Attractiveness (VA), which involves tangible design features like shape, color, materials, and interface (Yang et al., 2016). These elements influence perceived

enjoyment, emotional response, and social image, thereby shaping behavioral intention (Yang et al., 2016). Since wearables are incorporated into personal appearance and lifestyle, their visual appeal becomes a central source of satisfaction and a decisive factor in adoption (Choi & Kim, 2016).

Empirical findings consistently confirmed PA's positive effect on intention to adopt technologies. Users who find devices aesthetically pleasing are more likely to adopt them (Lee et al., 2020), and design appeal has been shown to enhance perceptions of social status, innovativeness, and self-identity (Chuah et al., 2016; Yang et al., 2016).

Overall, the evidence indicates that design is not a superficial consideration but a core aspect of perceived value. When consumers perceive a wearable as attractive and stylish, they form more favorable attitudes and stronger intentions to adopt, underlining the pivotal role of aesthetics in payment-only wearables. Therefore it is hypothesized that:

H8: Perceived Aesthetics positively influences behavioral intention to use payment only wearables.

2.3.9. Innovativeness (IN)

Innovativeness, often characterized as a personal trait, refers to an individual's willingness to try out new technologies and innovations (Agarwal & Prasad, 1998). Rogers (1983, 2003) defines an innovation as “an idea, practice or object that has distinct features which can be perceived as new” and classifies individuals according to the relative speed at which they adopt such innovations, highlighting the role of personal innovativeness as a distinguishing factor in adoption behavior. Innovativeness is thus, the degree to which an individual is open to new ideas and products and it plays a significant role in user acceptance of technology (Yi et al., 2006). It can also be understood as the degree to which an individual takes innovation decisions independently of SI (Midgley & Dowling, 1978). It has been consistently recognized as a key factor in early adoption behavior (Agarwal & Prasad, 1998; Yi et al., 2006), and more broadly, in explaining individual differences in technology acceptance. More innovative users are more likely to feel compatible with a technology and recognize its benefits (Oliveira et al., 2016).

Beyond its direct effects on adoption intention, innovativeness has also shown to play a moderating role in the relationships between various technology acceptance factors and adoption (Alenezi & Isa, 2022). Namely, innovativeness has been studied in prior technology adoption research to moderate the relationships between PE, EE, SI, CM and BI (Agarwal & Prasad, 1998, Jeon et al., 2020; Khazaei & Tareq, 2021, Dabholkar & Bagozzi, 2002), however it has not been consistently supported or rather rejected in most studies.

The moderating role of innovativeness in the link between PV and BI is ambiguous. Highly innovative consumers may pay a premium simply to try new technologies, suggesting a positive moderation (Dabholkar & Bagozzi, 2002). Yet, research also shows that innovators, being more informed and critical, can evaluate high prices negatively if the technology is seen as immature or lacking added utility (Im et al., 2008). Due to these two conflicting pathways, the overall moderation effect of innovativeness on Price Value is inconclusive and, therefore, this study does not propose a clear hypothesis for this path.

PA was also excluded from the moderation analysis, as innovativeness relates to novelty-seeking and technological openness rather than perceptions of beauty or design appeal.

Therefore, this study proposes that Innovativeness will moderate the effect PE, EE, CM, FC, TR and SI in the adoption of payment-only wearables. This addresses a gap in the literature on emerging payment devices, which calls to explore individual-difference moderators (Alenezi & Isa, 2022).

2.3.9.1. Innovativeness and Performance Expectancy

Highly innovative individuals are more predisposed towards new technologies and may, therefore, perceive greater benefits or utility from using them (Yi et al., 2006; Agarwal & Prasad, 1998; Thuy, 2023). This suggests that, for more innovative individuals, the perceived benefits, usefulness or performance gains of a technology are more easily envisioned and, therefore, have a stronger positive influence on their readiness to adopt that technology and integrate it into their routines (Moore, 1999; Rogers, 2003; Thuy, 2023). The rationale is that openness to change enhances perceived utility: when individuals are already inclined to try new things, they are also more

receptive to believing those things are useful. While Thuy (2023) found that employee innovativeness positively moderated the link between perceived usefulness and digital technology readiness (similar to BI), some authors did not find support for innovativeness moderating the relationship between PE and acceptance intention (Jeon et al., 2020) and Alkawsii et al., 2021). Despite these inconsistencies, the theoretical rationale supports the expectation of a positive moderation. Hence, it is hypothesized that:

H9: Innovativeness moderates the relationship between Performance Expectancy and Behavioral Intention to adopt wearable payment devices so that it is stronger for more innovative individuals.

2.3.9.2. Innovativeness and Effort Expectancy

Similarly, for EE, innovative individuals tend to be more willing to overcome initial difficulties or perceived complexity, or they may find more efficient pathways to learn and use new technologies (Yi et al., 2006). While Thuy (2023) found that employee innovativeness can positively moderate the relationship between perceived ease of use and digital technology readiness (similar to BI), other research has yielded different findings. Notably, Yi et al. (2006) consistently argued that innovativeness directly determines perceived ease of use rather than moderating its effect on behavioral intention. Furthermore, Jeon et al. (2020) and Alkawsii et al. (2021) found no support for innovativeness moderating the effect of EE on BI. However, innovative individuals are generally more tolerant of complexity, ambiguity, or learning curves because they see novelty as an opportunity rather than a barrier (Yi et al., 2006). Therefore, the perceived ease of use of a technology is likely to have a stronger positive effect on adoption intention for innovative users than for less innovative ones. Additionally, given their higher levels of knowledge, technical competence, and confidence in handling new tools, early adopters often perceive the same technology as easier to use and less challenging compared to later adopters (Moore, 1999; Rogers, 2003). This reinforces the expectation that innovativeness amplifies the impact of EE on BI for highly-innovative users, so it is hypothesized:

H10: Innovativeness moderates the relationship between effort expectancy and behavioral intention to adopt wearable payment devices, such that the relationship is stronger for more innovative individuals.

2.3.9.3. Innovativeness and Compatibility

Regarding CM, which reflects how consistent a technology is with an individual's lifestyle, needs, or values (Venkatesh et al., 2003), innovativeness may reinforce its influence on adoption. Generally, the more innovative a user is, the greater their propensity to perceive a new technology as compatible with their routines and identity, even when these technologies require some behavioral adaptation (Lu et al., 2005; Oliveira et al., 2016). While innovativeness is often considered an antecedent to CM, directly influencing how compatible a technology appears to a user (Yi et al., 2006), it could also act as a moderator, strengthening how compatibility translates into adoption behavior (Agarwal & Prasad, 1998). For example, highly innovative consumers are more likely to experiment with new ideas and technologies, making it easier for them to see how a payment-only wearable could seamlessly integrate into their daily routines and payment habits. Innovation diffusion theory further supports this view, emphasizing that early adopters can more easily envision the benefits of an innovation and relate it to their personal needs, making them more likely to see it as compatible compared to later adopters (Moore, 1999; Rogers, 2003). So, it is hypothesized that:

H11: Innovativeness moderates the relationship between compatibility and behavioral intention to adopt wearable payment devices such that the relationship is stronger for individuals with higher levels of Innovativeness.

2.3.9.4. Innovativeness and Facilitating Conditions

In consumer technology adoption contexts, FC captures the access to supportive infrastructure, compatibility with other systems, customer support (factors that can enhance the feasibility of adoption). Individuals with higher innovativeness tend to feel more confident in their own abilities

to overcome potential resource constraints, infrastructure gaps, or technical barriers (Agarwal & Prasad, 1998; Rogers, 2003). They are also more proactive in seeking information, experimenting with solutions, and adapting their environment to make a new technology work. This allows innovative users to capitalize more effectively on available FC and to adopt new technologies even in contexts where institutional or technical support may be limited. For instance Alenezi & Isa (2022), support this view, suggesting that highly innovative users are less discouraged by infrastructural gaps and more likely to perceive value in whatever support structures are available. This implies that for more innovative consumers, the presence of strong FC can have an amplified positive effect on their intention to adopt payment-only wearables, as they can leverage these resources more effectively than less innovative individuals. Hence, it is hypothesized:

H12: Innovativeness moderates the relationship between Facilitating Conditions and behavioral intention to adopt wearable payment devices such that the relationship is stronger for individuals with higher levels of Innovativeness.

2.3.9.5. Innovativeness and Trust

TR, a robust direct predictor for digital payments, reduces perceived risk and increases consumers' confidence in using new technologies (Gefen et al., 2003). However, individuals with high personal innovativeness tend to be more comfortable with uncertainty and more willing to experiment with unproven or emerging technologies (Agarwal & Prasad, 1998). This means that highly innovative consumers may be less deterred by potential trust concerns when deciding whether to adopt payment-only wearables (Jeon et al., 2020). Instead, TR can act as an even stronger enabler for these users, reinforcing their intention to adopt when they perceive the technology or provider as trustworthy (Alkawsi et al., 2021). In this sense, it is hypothesized that innovativeness strengthens the pathway from TR to behavioral intention by enhancing the effect of perceived trustworthiness among users who are already inclined to take risks and experiment.

H13: Innovativeness moderates the relationship between Trust and behavioral intention to adopt wearable payment devices such that the relationship is stronger for individuals with higher levels of Innovativeness.

2.3.9.6. Innovativeness and Social Influence

In most consumer technology adoption models, SI is theorized to exert a direct positive influence on BI, particularly in the early stages of innovation diffusion. According to Rogers (2003), innovators rely less on social approval and make independent decisions. They are less influenced by mainstream opinions and more by their own curiosity and intrinsic motivation (Agarwal & Prasad, 1998). From this perspective, one might expect SI to exert weaker influence on more innovative users.

However, some authors argue that innovators are trendsetters, highly sensitive to social cues, particularly in high-visibility consumption contexts, where early adoption enhances social identity or status (Dabholkar & Bagozzi, 2002; Lu, et al., 2005). Since payment-only wearables are devices worn on the body, even though the payment feature is hidden, the accessory itself is highly visible, allowing users to signal technological savviness or forward-thinking attitudes. Thus, it is hypothesized that more innovative individuals tend to care more about peers' opinions, strengthening the relationship between SI and behavioral intention.

H14: Innovativeness moderates the relationship between Social Influence and behavioral intention to adopt wearable payment devices such that the relationship is stronger for individuals with higher levels of Innovativeness.

2.4. Conceptual Model

The theoretical model, incorporating all the hypothesized relationships explained above, can be graphically represented as follows:

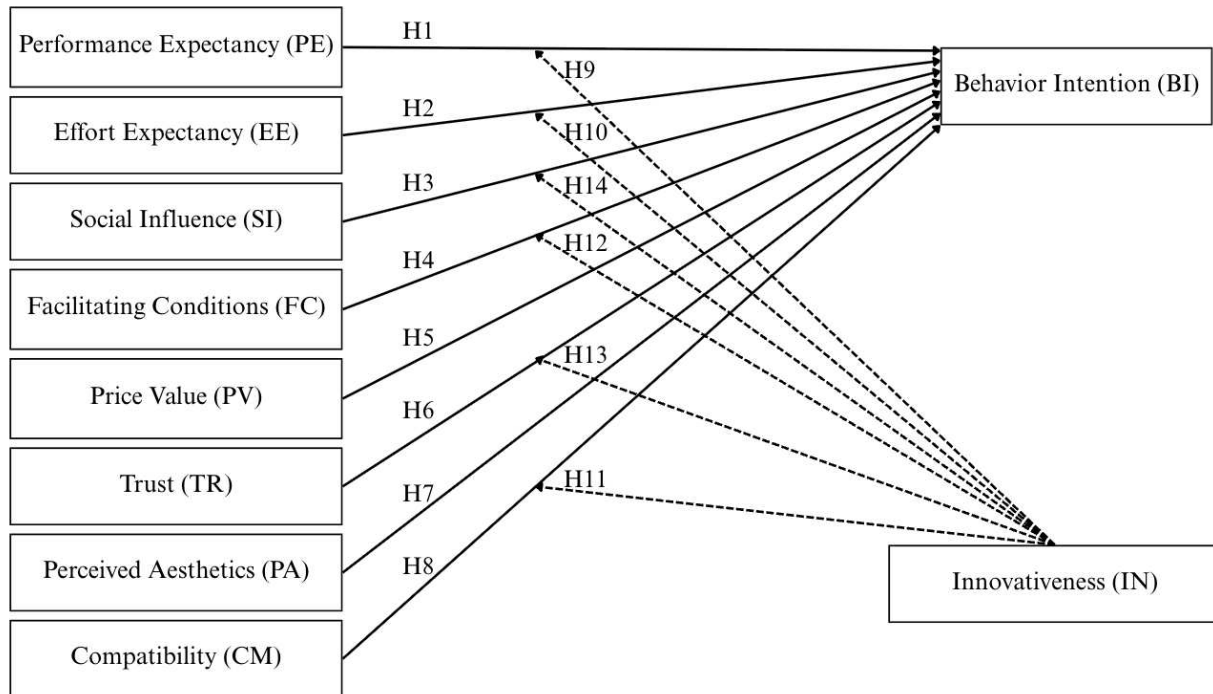


Figure 1: Conceptual Model

3. Methodology

3.1. Design

This study adopted a quantitative, cross-sectional research design, using a structured online questionnaire (Appendix 1) to investigate the factors influencing consumers' intention to adopt payment-only wearable devices. This approach was selected because it allows the collection of data from a large sample in a relatively short period of time and provides measurable information suitable for statistical hypothesis testing.

A quantitative approach offers several advantages, such as the ability to measure the strength and direction of relationships between variables and to evaluate the predictive power of multiple constructs through statistical modeling. However, it also presents limitations, such as the inability to capture in-depth motivations and the potential for self-report bias (Podsakoff et al., 2003). To mitigate these issues, the survey included clear and unambiguous item wording, an attention-check question to identify inattentive responses, and screening criteria to ensure participant relevance.

3.2. Participants and sampling

Data for this study was collected through a structured online questionnaire hosted on Qualtrics, which was open for responses between 16 and 23 of July 2024. The survey link was distributed via social media platforms (e.g., WhatsApp, Instagram) and direct messages to friends, family, and colleagues, encouraging voluntary participation.

A non-probability convenience sampling approach was employed, a common choice in exploratory technology adoption research due to its practicality, low cost, and ability to quickly reach a large number of participants. While this method does not ensure full representativeness of the general population, it was deemed appropriate for the explanatory aims of this thesis and the planned statistical analyses.

The target population consisted of adults aged 18 years or older who had at least one bank account with a physical or online financial institution, ensuring relevance to the topic of wearable payment

technology. At the beginning of the survey, respondents were required to provide informed consent and to confirm that they met the eligibility criteria before proceeding.

To assess whether the sample size would be sufficient for the main analysis technique (multiple linear regression) the guideline proposed by Green (1991) was considered. According to this rule, the required sample size should be $N > 50 + 8m$, where m represents the number of predictors. With eight predictors in this study, a minimum of 114 participants was necessary. This threshold was comfortably surpassed, with a total of 433 responses initially collected (254 in the final dataset), ensuring adequate statistical power for subsequent analyses.

3.3. Instrument Development

Each construct was measured using multiple items on a seven-point Likert scale ranging from 1 (strongly disagree) to 7 (strongly agree). Items were adapted from validated scales used in prior technology adoption research (e.g., Venkatesh et al., 2003; Venkatesh et al., 2012; Oliveira et al., 2016; Chuah et al., 2016; Liébana-Cabanillas et al., 2018; Al Mamun et al., 2023; Yang et al., 2016; Slade et al., 2015) to ensure content validity, while tailoring the wording and context specifically to payment-only wearable devices. The items used can be seen in Appendix 2.

The questionnaire was first developed in English and then translated into Portuguese to enhance accessibility for participants more comfortable with the local language. A back-translation process ensured conceptual equivalence between the two versions.

The questionnaire was structured as shown in table 1.

Section	Subject
1	Questionnaire Instruction
2	Payment Only Wearables
3	Perceptions
4	Demographic Information
5	Thank you for participating

Table 1: Structure of the questionnaire

3.4. Data Cleaning and Screening

Before data analysis, the dataset underwent a multi-step cleaning process to ensure validity, reliability and suitability for statistical testing. Of the 433 responses initially collected, several steps were taken to identify and remove invalid cases.

First, eligibility screening was applied. From the initial sample, a total of 111 responses were incomplete, 16 participants declined to provide consent, 12 were under 18 years old, and 4 did not have any bank account resulting in a dataset of 290 responses.

Second, an attention check question was included in the questionnaire to identify inattentive or careless responses. Out of the 290 participants, 30 failed the attention check, leaving a total of 260 valid responses.

Third, to further minimize the risk of careless or non-serious responses, a multivariate outlier detection was performed using Mahalanobis distance, which identifies cases that deviate significantly from the center of the multivariate distribution (Mahalanobis, 1936). The Mahalanobis distance values were evaluated against the chi-square distribution, and cases with p-values below the standard threshold ($p < .001$) were considered potential multivariate outliers. Accordingly, six cases were removed from the dataset, improving the normality and robustness of subsequent analyses, particularly for techniques such as multiple regression or moderation analysis, which are sensitive to multivariate anomalies (Appendix 3). After all cleaning procedures, the final dataset consisted of 254 responses used for analysis.

Additionally, reverse coding was applied to one item in innovativeness ("In general I am hesitant to try out new technologies.") to enhance interpretability, ensuring that higher scores consistently represented lower levels of innovativeness and vice versa.

3.5. Data Analysis Methodology

All statistical analyses were conducted using IBM SPSS Statistics (Version 30.0.0.0). A series of planned analytical procedures were designed to ensure the reliability and validity of the dataset and to test the research hypotheses.

3.5.1 Descriptive Statistics

Descriptive statistics were presented in tabular format to summarize both demographic variables and study constructs. For categorical variables (e.g. gender, age, education, country, and employment status), absolute and relative frequencies were reported. For continuous variables (the study constructs), descriptive indicators such as minimum, maximum, mean, and standard deviation were computed and reported. This step ensures a clear understanding of the sample composition and the general tendencies in responses.

3.5.2 Reliability Testing

To assess the internal consistency of the constructs used in the questionnaire, Cronbach's Alpha values were calculated for each multi-item scale. Cronbach's Alpha is one of the most widely used indicators of scale reliability, as it reflects the degree to which items in a given construct are interrelated and measure the same underlying concept. Interpretation typically follows established thresholds: values above 0.90 indicate excellent internal consistency, between 0.80 and 0.90 good, between 0.70 and 0.80 acceptable, between 0.60 and 0.70 weak, and below 0.60 inadmissible (Pestana & Gagueiro, 2014).

In addition to Cronbach's Alpha, corrected item-total correlations were examined for each scale to evaluate the contribution of individual items. Items with values below 0.40 were considered problematic and reviewed for removal (Loiacono et al., 2002) so that all final constructs met acceptable reliability thresholds, supporting the internal consistency of the measurement model.

3.5.3 Normality Assessment

Before conducting correlation analyses between the variables, the distribution of each construct was examined to assess normality. This step is crucial to determine the appropriate type of correlation coefficient to use, either parametric (Pearson) or non-parametric (Spearman).

Given the sample size of 254 participants, the assumption of normality was planned to be evaluated for each construct using the Kolmogorov-Smirnov test (50+ cases). In cases where non-normality

was indicated, skewness and kurtosis values were further examined. According to Kline (2023), skewness values below |3| and kurtosis below |8| indicate acceptable normality, meaning approximately normal distribution without serious deviations from normality. This step was essential to ensure the normal distribution of the constructs, thereby meeting the assumptions required for the use of parametric statistics (such as Pearson correlation).

3.5.5 Correlation Analysis

A Pearson correlation analysis was conducted to assess the strength and direction of the bivariate relationships among the study variables. The strength of the correlations was interpreted using the guidelines of Bryman and Cramer (2003), where coefficients are classified as follows: very low ($< .20$), low (.20–.39), moderate (.40–.59), high (.70–.89), and very high ($\geq .90$).

3.5.6 Multiple Linear Regression (MLR)

The primary statistical technique for hypothesis testing was Multiple Linear Regression, using the enter method to assess the combined predictive power of all eight independent variables on BI.

The assumptions of multiple linear regression were assessed prior to interpreting the model results. Regarding the independence of errors, the Durbin-Watson statistic has to fall within the acceptable range of 2 ± 0.5 , indicating that the residuals are uncorrelated. To assess multicollinearity, Tolerance and Variance Inflation Factor (VIF) values were examined. VIF values should be below the critical threshold of 5, and all Tolerance values should exceed 0.1 to confirm that multicollinearity is not a concern. The assumptions of linearity were evaluated graphically by examining the individual scatter plots of each independent variable against the dependent variable (BI) and homoscedasticity was evaluated by inspecting scatter plots of standardized predicted values against standardized residuals. Finally, the assumption of normality was evaluated by inspecting a histogram of the distribution of residuals, which should have a mean value of zero.

Regression coefficients (β), significance levels (p-values), and explained variance (R^2) will be reported for hypothesis testing.

3.5.7. Moderation Analysis

To evaluate the moderating effect of innovativeness on the relationships between PE, EE, SI, FC, TR, CM on BI, a moderation analysis was conducted using PROCESS macro v4.2 for SPSS (Hayes, 2022). This method enhances the reliability of the confidence intervals by resampling the dataset multiple times to account for variability in the data (Hayes, 2017).

4. Results & Discussion

4.1. Descriptive Statistics

4.1.1. Demographic Characteristics

The final sample consisted of 254 respondents. As shown in Appendix 4, the majority identified as female (65.0%), with males representing 34.3%, and 0.8% preferring not to disclose gender. The age distribution was relatively young, with the largest group aged 18–24 years (42.5%), followed by 25–34 years (27.2%), 35–44 years (13.4%), and smaller proportions in older age categories. Most participants resided in Portugal (80.7%), while the remaining 19.3% were distributed across several other countries. Regarding education, the majority held at least a bachelor's degree (61.8%), with 28.3% reporting a master's degree and 2.0% a doctorate. In terms of employment status, most participants were employed full-time (46.9%) or students (32.3%), with smaller percentages employed part-time (9.8%) or unemployed (7.9%).

The sample profile suggests a young, highly educated, Portugal-centered audience which is consistent with findings that younger, digitally literate consumers often represent the earliest adopters of emerging payment technologies (Venkatesh et al., 2012; Oliveira et al., 2016).

4.1.2. Construct Descriptives

Table 4.6 reports the descriptive statistics for the study constructs. Means across the constructs were generally above the midpoint, indicating a tendency toward agreement with the items. PE ($M = 5.97$, $SD = 1.04$) and EE ($M = 6.05$, $SD = 0.95$) exhibited the highest average scores, indicating respondents find payment-only wearables intuitive and believe they will improve transaction efficiency, consistent with prior evidence that ease of use and perceived usefulness strongly drive adoption of new technologies. TR ($M = 5.44$, $SD = 1.22$) and PV ($M = 5.31$, $SD = 1.18$) also scored relatively high, aligning with findings that security perceptions (Gefen et al., 2003) and favorable cost–benefit evaluations (Venkatesh et al., 2012) are central to intention formation. SI ($M = 3.62$, $SD = 1.62$) was the lowest-rated construct, reflecting weaker perceived pressure from others to adopt payment-only wearables.

SI is the only construct below neutral ($M \approx 3.62$), suggesting adoption intent may be more self-determined than norm-driven, echoing research showing that discretionary, personal technologies such as wearables are often less susceptible to normative pressures (Liébana-Cabanillas et al., 2018).

4.2. Reliability Analysis

The results of the reliability analysis are summarized in Appendix 5. PE (.949), SI (.959), TR (.923), PV (.925), CM (.945), PA (.956) and BI (.967) had Cronbach's Alphas higher than .900 indicating very good reliability. EE had a Cronbach's Alpha of .876 indicating a good internal consistency.

However, some constructs initially included items that reduced reliability. For example, one item from the FC scale ("If I had difficulties with setting up or using wearable payment devices I believe I could easily get assistance from a support team.") was removed due to a low item-total correlation (.336), which resulted in an increase in the overall alpha from .676 to .699, essentially at the .70 "reasonable" cut-off used in this thesis (Pestana & Gageiro, 2014). Similarly, IN initially had a lower alpha (.737), which improved to .855 ("good") after the removal of the item "In general I am hesitant to try out new technologies," which had a corrected item-total correlation of .227.

4.3. Assessment of Normality

The results of the normality assessment can be found in Appendix 6. As expected with large samples, the K-S test was statistically significant for all constructs ($p < .05$, most at $p < .001$), which formally rejects the null hypothesis of normality. However, the K-S test is known to be overly sensitive, often detecting even trivial deviations as significant. In contrast, the skewness and kurtosis indices for all constructs fell well within the thresholds.

Despite the rejection of normality by the K-S test, the analysis of skewness and kurtosis values indicated that the distributions can be considered approximately normal. Consequently, the

decision was made to proceed with Pearson's correlation coefficient to examine the linear relationships between the variables.

4.4. Correlation Analysis

The results revealed that all variables were positively and significantly correlated with BI at the $p < .05$ level, with varying levels of intensity (Appendix 7).

CM demonstrated the strongest positive correlation with BI ($r = .779, p < .001$), indicating a high-intensity relationship. This suggests that the more wearable payment devices align with consumers' lifestyles and routines, the more likely they are to intend to use them. (Rogers, 2003; Chuah et al., 2016).

PV also showed a high-intensity positive correlation ($r = .702, p < .001$), implying that favorable cost-benefit perceptions play a key role in behavioral intentions. PE ($r = .667, p < .001$), PA ($r = .655, p < .001$), SI ($r = .586, p < .001$), and TR ($r = .575, p < .001$) all exhibited moderate-intensity positive correlations with BI. These findings suggest that individuals are more likely to adopt wearable payment devices if they find them useful, visually appealing, socially encouraged, and trustworthy. IN showed a positive moderate correlation ($r = .496, p < .001$), suggesting that more innovative users may be more open to adopting new wearable payment technologies. FC correlated at a low positive intensity ($r = .308, p < .001$), indicating that while access to necessary resources and support has a positive effect, its influence on BI is limited. EE had a very low positive correlation ($r = .183, p = .003$) with BI. Although statistically significant, this result suggests that ease of use is only weakly related to users' intention to adopt wearable payment devices in this sample.

Looking beyond BI, the global correlation matrix revealed several strong and weak associations among the independent variables themselves.

The strongest overall correlation in the dataset was observed between CM and PE ($r = .715, p < .001$), suggesting that individuals who perceive wearable payment devices as compatible with their lifestyles also tend to view them as useful. Similarly strong associations were found between CM

and PV ($r = .702$), followed by CM and TR ($r = .648$), and CM and SI ($r = .627$), reinforcing the central role of compatibility in users' overall perceptions.

TR also correlated moderately with PV ($r = .566$) and SI ($r = .539$), indicating that trust in the technology enhances both price value and receptiveness to others' opinions.

At the opposite end of the spectrum, the weakest correlation in the matrix was found between EE and PA ($r = .067$, $p = .284$), which was also the only correlation that was not statistically significant. This suggests that ease of use and aesthetic appeal are largely unrelated dimensions in the context of wearable payment devices. Another notably weak relationship was observed between EE and PV ($r = .135$, $p = .031$), further suggesting that ease of use is not closely tied to users' perceptions of financial worth.

In general, the pattern of correlations indicates that CM, PV, TR, and SI are central and interconnected variables within the model, while EE appears to be more isolated and less influential both in relation to BI and across the broader network of constructs.

4.5. Multiple Linear Regression Analysis

4.5.1. Multiple Linear Regression Results

4.5.1.1. Model Fit

The overall model was statistically significant ($F(8, 245) = 73.54$, $p < .001$) and explained a substantial proportion of the variance in BI ($R^2 = .706$; Adjusted $R^2 = .696$). This indicates that approximately 70.6% of the variation in BI can be accounted for by the combination of the independent variables included in the model.

Model Summary^b

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,840 ^a	,706	,696	1,02682	1,830

a. Predictors: (Constant), Perceived Aesthetics, Effort Expectancy, Social Influence, Facilitating Conditions, Performance Expectancy, Trust, Price Value, Compatibility

b. Dependent Variable: Behavioral Intention

Table 2: Multiple Linear Regression Results

4.5.1.2. Assumptions Check

The assumptions of multiple linear regression were verified (see Appendix 8), namely: independence of errors (Durbin–Watson = 1.830, within acceptable limits), absence of multicollinearity (all VIF < 5; Tolerance > 0.1), linearity and homoscedasticity (scatter plots of independent vs. dependent variables and scatterplots of standardized predicted values vs. residuals showed no curvature or funneling), normal distribution of residuals (histogram indicated no substantial skewness or kurtosis; residuals' mean \approx 0.000), and lack of influential outliers (only one standardized residual slightly above ± 3 , but without undue influence). Overall, all key assumptions were satisfactorily met.

4.5.1.3. Interpretation of Coefficients

The regression coefficients revealed that six of the eight predictors had a statistically significant effect on behavioral intention.

PE had a significant positive effect ($\beta = .167$, $p = .001$), leading to the acceptance of H1. EE was not significant ($\beta = -.073$, $p = .109$), resulting in the rejection of H2. Both SI ($\beta = .095$, $p = .044$) and FC ($\beta = .089$, $p = .046$) showed weak but significant effects supporting H3 and H4. PV was a significant predictor ($\beta = .173$, $p = .001$), supporting H5. TR, however, was not significant ($\beta = .045$, $p = .363$), leading to the rejection of H6. CM emerged as the strongest predictor ($\beta = .309$, $p < .001$), supporting H7, followed by PA, which also demonstrated a strong effect ($\beta = .208$, $p < .001$), supporting H8.

Overall, the analysis indicates that CM, PA, PV and PE were the most influential determinants of behavioral intention, while SI and FC played smaller but significant roles. In contrast, EE and TR did not contribute significantly to the model.

H#	Hypothesis	Result (supported/not supported)
1	Performance Expectancy positively influences the Behavioral Intention to use payment-only wearables.	Supported
2	Effort Expectancy positively influences the Behavioral Intention to use payment-only wearables.	Not Supported
3	Social Influence positively influences the Behavioral Intention to use payment-only wearables.	Supported
4	Facilitating Conditions positively influences the Behavioral Intention to use payment-only wearables.	Supported
5	Price Value positively influences the Behavioral Intention to use payment-only wearables.	Supported
6	Trust positively influences the Behavioral Intention to use payment-only wearables.	Not Supported
7	Compatibility positively influences the Behavioral Intention to use payment-only wearables.	Supported
8	Perceived Aesthetics positively influences the Behavioral Intention to use payment-only wearables.	Supported

4.5.2. Discussion of MLR’s Results (H1-H8)

CM emerged as the strongest predictor of adoption, confirming H7. This result is consistent with DOI theory (Rogers, 2003) and prior studies showing that lifestyle fit is crucial for consumer acceptance of voluntary technologies (Oliveira et al., 2016; Al Mamun et al., 2023). Payment-only wearables, being accessories worn on the body, are evaluated in terms of how seamlessly they can be integrated into daily life. The dominance of compatibility suggests that beyond technical performance, consumers adopt these devices when they can imagine them as natural extensions of their routines and identity.

PA was also highly significant, supporting H8, and reinforcing the dual role of wearables as both payment tools and fashion statements. This aligns with the concept of “fashnology” (Chuah et al., 2016) and with evidence that design appeal plays a critical role in shaping adoption of technologies (Lee et al., 2020; Yang et al., 2016) where the aesthetic dimension promotes adoption intention in contexts where technologies are worn on the body and become visible markers of lifestyle.

Together with compatibility, aesthetics highlights that adoption is driven not only by what the device does but also by how it looks and fits into consumers' lifestyles.

PE, supporting H1, was also a significant determinant. Consistent with UTAUT2 (Venkatesh et al., 2012) and prior studies across digital and mobile payments (Oliveira et al., 2016; Ooi & Tan, 2016; Pal et al., 2015), this finding reinforces the idea that consumers primarily assess new payment technologies based on their ability to deliver speed, efficiency, and reliability in transactions. The result also aligns with studies on wearable payments that identified usefulness as a critical adoption driver (Chuah et al., 2016; Lee et al., 2020).

Price value, confirming H5, further illustrates the relevance of utilitarian evaluations. The significant effect aligns with UTAUT2's cost-benefit logic (Venkatesh et al., 2012) and prior findings that favorable value perceptions increase adoption (Al-Okaily et al., 2020). Yet, the role of PV has not always been consistent, with some studies reporting non-significance (Slade et al., 2015; Neves et al., 2025; Tan et al., 2014). Its importance here may reflect an early-stage adoption context, where consumers actively weigh the added value of wearables against established alternatives such as cards or smartphones. However, as adoption matures, PV may decline in importance, with lifestyle or incentive-related drivers gaining greater weight (Islam et al., 2024).

SI and FC both showed weak but significant effects, supporting H3 and H4. This indicates that while peer encouragement and resource sufficiency contribute to adoption, they play a secondary role compared to lifestyle and utilitarian drivers.

For SI, this result contrasts with studies that reported stronger normative pressures in mobile and NFC payments (Oliveira et al., 2016; Slade et al., 2015; Liébana-Cabanillas et al., 2018) but aligns with more recent research showing SI to be limited in discretionary, consumer-driven contexts (Belanche et al., 2022; Islam et al., 2024). Unlike Al Mamun et al. (2023), who found a negative SI effect among Malaysian youth, the current result suggests that social cues play a supportive but not decisive role. Although SI displayed a moderate correlation with BI, its unique predictive effect was overshadowed in the regression model. This indicates that while SI does matter in shaping adoption intention, much of its effect might have been overlapped with stronger predictors such as compatibility and aesthetics. A possible explanation is that wearables, being highly personal and tied to self-expression, are adopted more on the basis of individual preference than peer approval,

meaning individuals who feel socially encouraged to adopt wearables can be the same people who already perceive them as fitting their lifestyle or attractive in design. Once those lifestyle and design factors are accounted for, SI contributes little additional explanatory power. Another possible explanation is that, since payment-only wearables remain niche products in this mainly Portuguese sample, social cues have not yet reached a critical mass to exert stronger influence.

For FC, the findings are consistent with UTAUT2 (Venkatesh et al., 2012) and studies highlighting the role of resource sufficiency and infrastructure (Song et al., 2023; Patil et al., 2020; Tang & Tsai, 2024), while also resonating with research where FC showed little or no effect (Slade et al., 2015; Oliveira et al., 2016; Islam et al., 2024). Its modest effects are consistent with its low correlation with BI, indicating that its influence is genuinely limited rather than suppressed by other constructs. This suggests that access to resources and infrastructure exerts only a marginal influence on intention. Especially in Portugal (the majority of the sample), where NFC infrastructure is already widespread, most consumers assume that terminals and support exist, which means FC does not strongly differentiate adopters from non-adopters. Thus, while FC matters, its impact on BI is limited once other, more evaluative constructs are considered.

By contrast, EE was not significant, leading to the rejection of H2. This outcome highlights the diminishing role of constructs once central to adoption. While EE's lack of significance contradicts strongly with some studies (Madan & Yadav, 2016) it aligns with research suggesting that ease of use becomes less relevant once consumers are familiar with mobile technologies (King & He, 2006; Oliveira et al., 2016; Al-Okaily et al., 2020). Its low correlation with BI suggests that there is in fact a limited influence of this factor rather than it being overshadowed by other constructs, Ease of use has little bearing on adoption in this sample. For digitally literate consumers, wearables being "easy" is assumed, it is a baseline expectation, not a selling point (Rouibah et al., 2016; Liu et al., 2019). Because EE is both weakly correlated and weak in regression, it is not being masked or absorbed by stronger constructs; it is simply not important in this adoption context.

Unexpectedly, TR (H6) was also not significant in the regression, despite its robust theoretical and empirical support in mobile and electronic payment research (Gefen et al., 2003; Patil et al., 2020; Marriott & Williams, 2018). While, TR showed a positive correlation with BI, in the multiple linear regression, their explanatory power was overshadowed by stronger predictors such as

compatibility and PE and CM. This indicates that while TR is positively related to adoption intention, its explanatory power is largely absorbed by these stronger predictors. In other words, consumers who trust wearable payments may be the same individuals who already perceive them as useful and well aligned with their lifestyle. Once these evaluative factors are considered, TR adds little unique contribution. As a result, TR operates more as a hygiene factor, meaning that although security and reliability remain essential preconditions, they are treated as baseline expectations rather than decisive motivators in the adoption of payment-only wearables. This may be particularly true for younger, digitally literate users, who assume secure infrastructure as a given (Zhou et al., 2010; Rouibah et al., 2016; Liu et al., 2019).

4.6. Moderation Analysis

4.6.1. Moderation Results

4.6.1.1. Moderation of IN on the relationship between PE and BI

The model explains 55.76% ($R^2 = 0.5576$) of the variance in respondents' behavioral intention to adopt wearable payment devices, with this value being statistically significant ($F(3, 250) = 105.0327$; $p < 0.001$). Both PE ($B = 0.6927$; $t = 12.6661$; $p < 0.001$) and IN ($B = 0.3932$; $t = 6.7813$; $p < 0.001$) have a significant positive effect on BI, indicating that the higher the PE/IN, the greater the BI.

Finally, the results reveal that IN significantly moderates the relationship between PE and BI ($B = 0.1608$; $t = 4.4815$; $p < 0.001$), with this effect being positive. As shown in Figure 9.1, the higher the respondents' innovativeness, the stronger the effect of PE on BI, thus supporting H9. The effect of PE on BI is statistically significant at all levels of respondents' IN, namely low ($B = 0.4601$; $t = 6.2275$; $p < 0.001$), medium ($B = 0.6927$; $t = 12.6661$; $p < 0.001$), and high innovativeness ($B = 0.9253$; $t = 12.0348$; $p < 0.001$).

		Unstandardized Coeficientes			
		B	Std. Error	t	Sig.
(Constant)		3,8027	0,0831	45,7639	<0,001
Performance Expectancy		0,6927	0,0547	12,6661	<0,001
Innovativeness		0,3932	0,0580	6,7813	<0,001
PE * Innovativeness		0,1608	0,0359	4,4815	<0,001
R ² =0,5576		F _(3, 250) = 105,0327	p<0,001	N=254	
Innovativeness	Baixa	0,4601	0,0739	6,2275	<0,001
	Média	0,6927	0,0547	12,6661	<0,001
	Elevada	0,9253	0,0769	12,0348	<0,001

Dependent Variable: Behavioral Intention

4.6.1.2. Moderation of IN on the relationship between EE and BI

The model explains 24.93% ($R^2 = 0.2493$) of the variance in respondents' behavioral intention to adopt wearable payment devices, with this value being statistically significant ($F(3, 250) = 27.6757$; $p < 0.001$). EE has a negative but not statistically significant effect on BI ($B = -0.1480$; $t = -1.0318$; $p = 0.3032$) and IN has a significant positive effect on BI ($B = 0.6724$; $t = 8.4767$; $p < 0.001$), indicating that the higher the IN, the greater the BI to adopt wearable payment devices.

Finally, the results reveal that innovativeness does not significantly moderate the relationship between EE and BI ($B = -0.0650$; $t = -0.8154$; $p = 0.4156$). As shown in Figure 9.2, although higher IN among respondents is associated with a weaker effect of EE on BI, this negative effect of IN does not emerge as statistically significant. Meaning H10 was not supported.

		Unstandardized Coeficientes			
		B	Std. Error	t	Sig.
(Constant)		3,8027	0,0831	45,7639	<0,001
Effort Expectancy		-0,1480	0,1434	-1,0318	0,3032
Innovativeness		0,6724	0,0793	8,4767	<0,001
EE * Innovativeness		-0,0650	0,0797	-0,8154	0,4156
R ² =0,2493		F _(3, 250) = 27,6757	p<0,001	N=254	

Dependent Variable: Behavioral Intention

4.6.1.3. Moderation of IN on the relationship between CM and BI

The model explains 64.57% ($R^2 = 0.6457$) of the variance in respondents' behavioral intention to adopt wearable payment devices, with this value being statistically significant ($F(3, 250) = 151.8611$; $p < 0.001$). Both CM ($B = 0.8030$; $t = 16.6667$; $p < 0.001$) and IN ($B = 0.2006$; $t =$

3.5904; $p < 0.001$) have a significant positive effect on BI, indicating that the higher the CM/IN, the greater the behavioral intention to adopt wearable payment devices.

Finally, the results reveal that IN significantly moderates the relationship between CM and BI ($B = 0.1192$; $t = 4.0383$; $p < 0.001$), with this effect being positive. As shown in Figure 9.3, the higher the respondents' innovativeness, the stronger the effect of CM on BI. The effect of CM on BI is statistically significant at all levels of respondents' IN, namely low ($B = 0.6307$; $t = 10.4201$; $p < 0.001$), medium ($B = 0.8030$; $t = 16.6667$; $p < 0.001$), or high ($B = 0.9754$; $t = 14.3473$; $p < 0.001$). Thus confirming H11.

		Unstandardized Coefficients			
		B	Std. Error	t	Sig.
(Constant)		3,7852	0,0785	48,2455	<0,001
Compatibility		0,8030	0,0482	16,6667	<0,001
Innovativeness		0,2006	0,0559	3,5904	<0,001
C * Innovativeness		0,1192	0,0295	4,0383	<0,001
R ² =0,6457		F _(3, 250) = 151,8611	p<0,001	N=254	
Innovativeness	Low	0,6307	0,0605	10,4201	<0,001
	Medium	0,8030	0,0482	16,6667	<0,001
	High	0,9754	0,0680	14,3473	<0,001

Dependent Variable: Behavioral Intention

4.6.1.4. Moderation of IN on the relationship between FC and BI

The model explains 25.72% ($R^2 = 0.2572$) of the variance in respondents' behavioral intention to adopt wearable payment devices, with this value being statistically significant ($F(3, 250) = 28.8533$; $p < 0.001$). FC has a marginally significant positive effect on BI ($B = 0.2524$; $t = 1.9660$; $p = 0.0504$) and IN has a significant positive effect on BI ($B = 0.5726$; $t = 7.2359$; $p < 0.001$), indicating that the higher the IN, the greater the BI to adopt wearable payment devices.

Finally, the results reveal that IN does not significantly moderate the relationship between FC and BI ($B = 0.0721$; $t = 1.0052$; $p = 0.3158$), rejecting H12. As shown in Figure 9.4, at all levels of IN, an increase in FC positively impacts BI, increasing it. However, this impact is similar for low, medium, and high innovativeness. It can be noted that at low, medium, or high levels of FC, individuals with high IN consistently show higher BI, while those with low IN consistently show lower BI.

	Unstandardized Coefficients		t	Sig.
	B	Std. Error		
(Constant)	3,8803	0,1120	34,6493	<0,001
Facilitating Conditions	0,2524	0,1284	1,9660	0,0504
Innovativeness	0,5726	0,0791	7,2359	<0,001
FC * Innovativeness	0,0721	0,0718	1,0052	0,3158
R ² =0,2572		F _(3, 250) = 28,8533	p<0,001	N=254

Dependent Variable: Behavioral Intention

4.6.1.5. Moderation of IN on the relationship between TR and BI

The results are presented in Table H13 and Figure H13.2, showing that the model explains 41.40% ($R^2 = 0.4140$) of the variance in respondents' behavioral intention, with this value being statistically significant ($F(3, 250) = 58.8650$; $p < 0.001$). Both TR ($B = 0.5341$; $t = 8.0728$; $p < 0.001$) and IN ($B = 0.4007$; $t = 5.7567$; $p < 0.001$) have a significant positive effect on BI, indicating that the higher the TR/IN, the greater the BI to adopt wearable payment devices.

Finally, the results reveal that IN significantly moderates the relationship between TR and BI to adopt wearable payment devices ($B = 0.0826$; $t = 2.0729$; $p = 0.039$), with this effect being positive. As shown in Figure 9.5, the higher the IN, the stronger the effect of TR on BI to adopt wearable payment devices, supporting H13. The effect of TR on BI is statistically significant at all levels of IN, namely when IN is low ($B = 0.4146$; $t = 4.5868$; $p < 0.001$), medium ($B = 0.5341$; $t = 8.0728$; $p < 0.001$), or high ($B = 0.6536$; $t = 7.6850$; $p < 0.001$).

		Unstandardized Coefficients		t	Sig.
		B	Std. Error		
(Constant)		3,8490	0,0978	39,3496	<0,001
Trust		0,5341	0,0662	8,0728	<0,001
Innovativeness		0,4007	0,0696	5,7567	<0,001
Trust * Innovativeness		0,0826	0,0399	2,0729	0,039
R ² =0,4140		F _(3, 250) = 58,8650	p<0,001	N=254	
Innovativeness	Low	0,4146	0,0904	4,5868	<0,001
	Medium	0,5341	0,0662	8,0728	<0,001
	High	0,6536	0,0851	7,6850	<0,001

Dependent Variable: Behavioral Intention

4.6.1.6. Moderation of IN on the relationship between SI and BI

This model explains 46.13% ($R^2 = 0.4613$) of the variance in respondents' behavioral intention, with this value being statistically significant ($F(3, 250) = 71.3587$; $p < 0.001$). Both SI ($B = 0.5330$; $t = 9.4247$; $p < 0.001$) and IN ($B = 0.4693$; $t = 7.2103$; $p < 0.001$) have a significant positive effect on BI, indicating that the higher the SI/IN, the greater the BI to adopt wearable payment devices.

Finally, the results reveal that IN significantly moderates the relationship between SI and BI to adopt wearable payment devices ($B = 0.1057$; $t = 3.0289$; $p = 0.002$), with this effect being positive, confirming H14. As shown in Figure 9.6, the higher the IN, the stronger the effect of SI on BI. The effect of SI on BI is statistically significant at all levels of respondents' IN, namely when IN is low ($B = 0.3802$; $t = 4.9329$; $p < 0.001$), medium ($B = 0.5330$; $t = 9.4247$; $p < 0.001$), or high ($B = 0.6859$; $t = 9.2061$; $p < 0.001$).

	Unstandardized Coefficients				
	B	Std. Error	t	Sig.	
(Constant)	3,8426	0,0908	42,2993	<0,001	
Social Influence	0,5330	0,0566	9,4247	<0,001	
Innovativeness	0,4693	0,0651	7,2103	<0,001	
SI * Innovativeness	0,1057	0,0349	3,0289	0,002	
$R^2=0,4613$ $F_{(3, 250)}= 71,3587$ $p<0,001$ $N=254$					
Innovativeness	Low	0,3802	0,0771	4,9329	<0,001
	Medium	0,5330	0,0566	9,4247	<0,001
	High	0,6859	0,0745	9,2061	<0,001

Dependent Variable: Behavioral Intention

H#	Hypothesis	Result (supported/not supported)
9	Innovativeness moderates the relationship between Performance Expectancy and Behavioral Intention to adopt wearable payment devices so that it is stronger for more innovative individuals.	Supported
10	Innovativeness moderates the relationship between Effort Expectancy and Behavioral Intention to adopt wearable payment devices so that it is stronger for more innovative individuals	Not Supported
11	Innovativeness moderates the relationship between Compatibility and Behavioral Intention to adopt wearable payment devices so that it is stronger for more innovative individuals	Supported
12	Innovativeness moderates the relationship between Facilitating Conditions and Behavioral Intention to adopt wearable payment devices so that it is stronger for more innovative individuals	Not Supported
13	Innovativeness moderates the relationship between Trust and Behavioral Intention to adopt wearable payment devices so that it is stronger for more innovative individuals	Supported
14	Innovativeness moderates the relationship between Social Influence and Behavioral Intention to adopt wearable payment devices so that it is stronger for more innovative individuals	Supported

4.6.2. Discussion of Moderation Effects (H9-H14)

Innovativeness positively moderates the PE-BI relationship, meaning innovative individuals' strong perception of benefits more significantly drives their adoption intention. This aligns with Thuy (2023) who found a similar positive moderation of perceived usefulness (similar to PE) on readiness. However, this contradicts Yi et al. (2006), who consistently found that innovativeness acts as a direct determinant of usefulness rather than a moderator, and Alkawsii et al. (2021), who did not support this moderating hypothesis.

The rejection of IN's moderating role in the EE-BI relationship suggests that for innovative users, ease of use does not differentially impact their adoption intention. This is because innovative individuals often perceive new technologies as inherently easier to use (Yi et al., 2006; Lu et al., 2005). This result aligns with Yi et al. (2006), Jeon et al. (2020), and Alkawsii et al. (2021), all of whom found no significant moderating effect of innovativeness on EE's influence on intention. Conversely, Thuy (2023) found a positive moderating effect of innovativeness on the perceived ease of use and digital technology readiness relationship, showing a contextual divergence.

Innovativeness positively moderates the CM-BI relationship, indicating that for innovative individuals, a perceived fit with their lifestyle more strongly translates into adoption. This is because innovators are more prone to envision how new technologies integrate into their routines (Lu, et al., 2005; Oliveira et al., 2016) and easily relate innovation benefits to personal needs (Rogers, 2003; Moore, 1999). This result partially supports Agarwal & Prasad (1998) who found initial support for this moderation. However, it contrasts with Yi et al. (2006), who consistently concluded that innovativeness directly determines perceived compatibility rather than moderating its effect on intention.

The moderating role of innovativeness in the FC-BI relationship was rejected. This suggests that an innovative individual's intention to adopt is not differentially affected by the availability of resources or support structures. This aligns with Jeon et al. (2020), who explicitly rejected this hypothesis. While Alenezi & Isa (2022) found innovativeness to moderate the relationship between organizational readiness (a related construct) and e-commerce adoption, this was a specific organizational context and not direct support for FC and BI. It's worth noting that Oliveira et al. (2016) found FC itself to be an insignificant predictor of behavioral intention.

Innovativeness positively moderates the TR-BI relationship, implying that for highly innovative individuals, TR is a stronger enabler of adoption. While innovators are comfortable with uncertainty (Agarwal & Prasad, 1998), robust trust can amplify their inherent willingness to experiment. Jeon et al. (2020) supports this indirectly by finding that innovativeness decreases the negative influence of perceived risk (inversely related to TR) on acceptance intention. However, Alkawsii et al. (2021) presented a nuanced contradictory finding, showing that highly innovative individuals were more sensitive to high privacy concerns (a trust-related risk), leading to a greater reduction in their intention.

Innovativeness positively moderates the SI-BI relationship, suggesting that for highly innovative users, peer opinions and recommendations more strongly influence their adoption. This supports the "innovators as trendsetters" perspective, especially for visible technologies like wearables. This finding is directly supported by Jeon et al. (2020), who found that higher innovativeness strengthens the influence of SI on acceptance intention. Conversely, this contradicts Rogers (2003) and Agarwal & Prasad (1998), who argue that innovators are less influenced by social approval. Similarly, Lu et al. (2005) found innovators to be less influenced by social connections, and Khazaei & Tareq (2021) concluded that highly innovative individuals are more likely to ignore social norms. This suggests a context-dependent role for innovativeness regarding SI.

5. Conclusion

This study set out to examine the determinants of consumers' behavioral intention (BI) to adopt payment-only wearable devices, extending the UTAUT2 framework with trust, compatibility, and perceived aesthetics, and testing innovativeness as a moderator. The model demonstrated strong explanatory power, accounting for 70.6% of the variance in BI, confirming its suitability for analyzing emerging payment technologies.

These findings reveal a shift in adoption dynamics. Traditional utilitarian factors such as usefulness and value remain important, but they are now accompanied and in some cases even surpassed by lifestyle and design-related drivers. At the same time, ease of use and trust, once central in digital payment adoption, appear to have become "taken for granted" qualities rather than differentiators. This suggests that as technologies mature, determinants of adoption shift away from functional simplicity and security toward lifestyle alignment and aesthetics.

The moderation analysis further revealed the role of personal innovativeness in shaping adoption behavior. Innovativeness significantly strengthened the effects of PE, CM, TR, and SI on BI, confirming that more innovative individuals are both more receptive to usefulness and lifestyle fit, and more responsive to trust cues and peer opinions. By contrast, innovativeness did not moderate the effects of EE or FC, indicating that openness to innovation does not influence perceived ease of use or infrastructure availability. These findings emphasize that innovative consumers act as trendsetters, amplifying the influence of certain adoption drivers and providing valuable insights for targeting early adopter segments.

5.1. Theoretical Contributions

This study advances the theoretical understanding of technology adoption by extending the UTAUT2 framework with compatibility, trust, and aesthetics, and by introducing innovativeness as a key individual-difference moderator. In doing so, it demonstrates that consumer adoption of payment-only wearables cannot be fully explained by functional determinants alone, but must also account for lifestyle alignment, perceptions of trustworthiness, and design appeal. The findings highlight that technology adoption is a dynamic process that evolves alongside consumer

expectations and market maturity: while early adoption is driven by performance and effort-related concerns, later stages of diffusion place greater emphasis on identity expression, social signaling, and aesthetic integration. By addressing these emerging dimensions, this research contributes to a more holistic theoretical model of consumer adoption in the context of wearable financial technologies.

5.2. Managerial Contributions

From a managerial perspective, the findings provide actionable insights for firms operating in the wearable payments market. Beyond emphasizing efficiency and convenience, businesses should strategically position payment-only wearables as lifestyle-enhancing tools that integrate seamlessly into consumers' daily routines. Product design should prioritize aesthetics, personalization, and symbolic value, enabling consumers to use wearables not only as payment instruments but also as expressions of identity and social status. Marketing strategies can leverage social influence by engaging early adopters, influencers, and peer networks to accelerate diffusion among innovative consumer segments. While competitive pricing remains relevant, firms should avoid competing primarily on cost; instead, communication efforts should highlight value derived from usability, reliability, trust, and seamless ecosystem integration. Collectively, these insights help managers translate consumer adoption drivers into concrete design, branding, and go-to-market strategies for wearable payment devices.

5.3. Limitations and Suggestions for Future Research

Several limitations should be acknowledged. First, the study examined behavioral intention rather than actual usage, which limits insights into post-adoption behavior. Second, reliance on a cross-sectional, self-reported, and convenience-based sample restricts generalizability, particularly beyond the predominantly young, educated, Portugal-based respondents. Third, the analysis was conducted using multiple regression and separate moderation tests, which did not capture interrelationships within a full structural model. Future research should address these gaps by adopting longitudinal and cross-cultural approaches, exploring adoption drivers across demographic segments, and integrating emerging factors such as sustainability perceptions, interoperability, and biometric authentication.

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Appendices

Appendix 1: Questionnaire



Survey Flow

Block: First Block: Introduction | Primeiro Bloco: Introdução (4 Questions)
Standard: Second Block: Payment-Only Wearables | Segundo Bloco: Wearables de Pagamento (2 Questions)
Standard: Third Block: Perceptions | Terceiro Bloco: Percepções (12 Questions)
Standard: Fourth Block: Demographic Information | Quarto Bloco: Informações Demográficas (6 Questions)

Page Break

Start of Block: First Block: Introduction | Primeiro Bloco: Introdução

Hello and welcome! My name is Carolina Almeida, and I am a Master's student at Católica Lisbon School of Business and Economics. I am conducting this research as part of my Master's thesis. The goal of this study is to better understand what influences people's intention to adopt new payment solutions.

Participation is voluntary and your answers will remain completely anonymous and used solely for academic purposes. The survey will take approximately 7-8 minutes to complete.

There are no right or wrong answers—please answer as honestly and accurately as possible based on your own views and experience. If you have any questions, please feel free to reach out at: s-casisaalmeida@ucp.pt Thank you very much for your participation!

Q1 Do you consent to participate in this study?

- No (1)
- Yes (2)

Skip To: End of Survey If Q1 = 1

Q2 Are you 18 years old or older?

- No (1)
- Yes (2)

Skip To: End of Survey If Q2 = 1

Q24 Do you have a bank account (with any bank, Revolut, Wise or any other similar financial services operator)?

- No (1)
- Yes (2)

We'll be discussing payment-specific wearables. What are these devices? These are accessories such as wristbands, rings, keychains, or watch straps that contain a built-in contactless payment chip.

- ✔ Pay by simply tapping - no phone, battery or internet needed when paying.
- ✔ Link it once with your bank card, payment app or secure website using your smartphone.
- ✔ After the initial setup, you only need your phone to check balance or update settings.
- ✔ Works with any terminal that accepts other contactless payments (contactless cards, Apple Pay, etc).

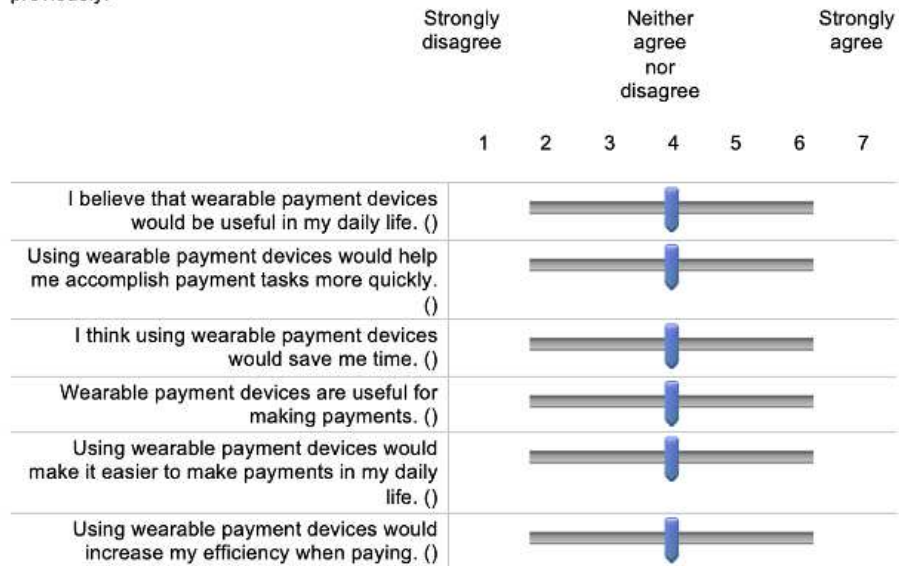
Please take a moment to carefully look at the examples below, which include different brands, designs, materials, features, and prices.



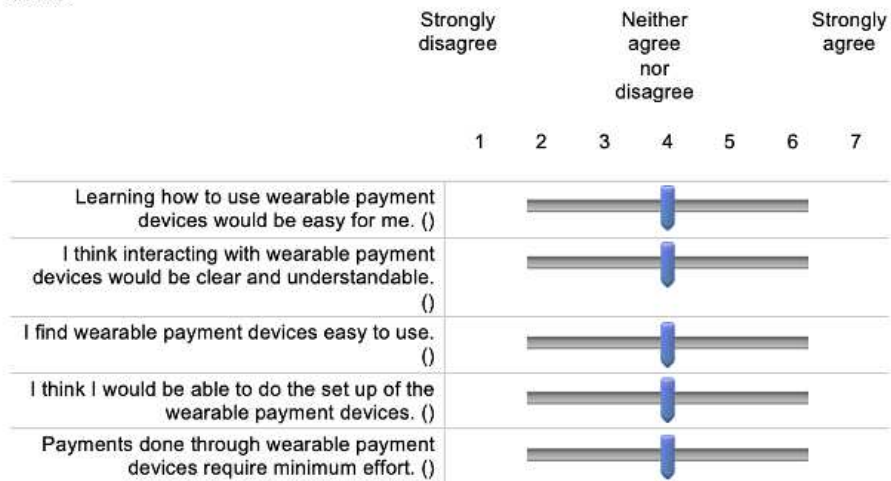
Please watch the following video (very short) that shows how payments work with wearables similar to the ones you saw above.



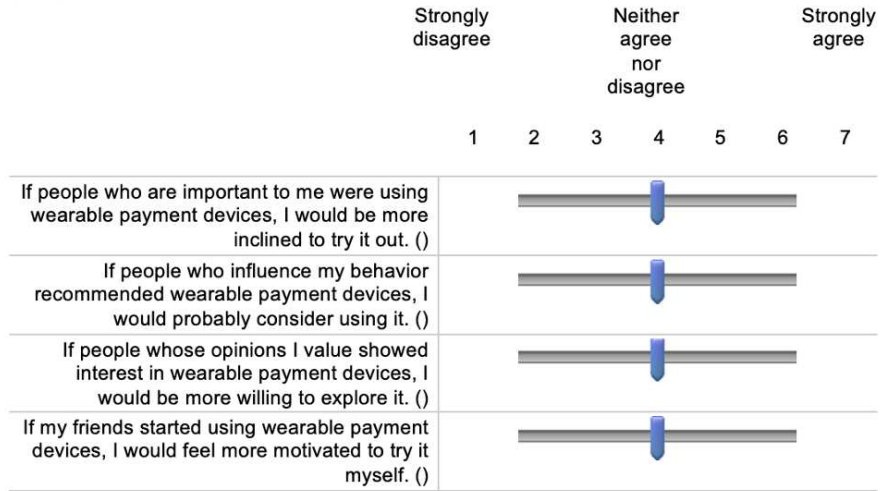
Q4 PE On a scale from 1 (strongly disagree) to 7 (strongly agree), please indicate how much you agree or disagree with the following statements about the wearable payment devices shown previously.



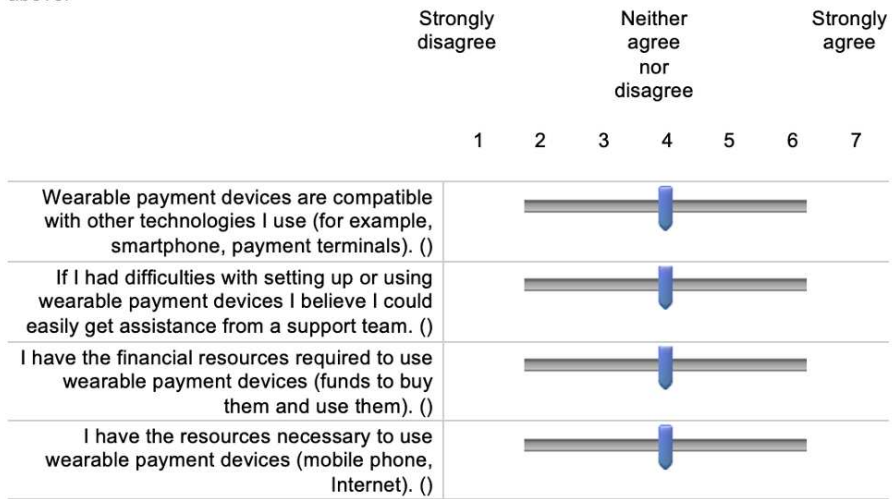
Q5 EE On a scale from 1 (strongly disagree) to 7 (strongly agree), please indicate how much you agree or disagree with the following statements about the wearable payment devices shown above.



Q6 SI On a scale from 1 (strongly disagree) to 7 (strongly agree), please indicate how much you agree or disagree with the following statements about the wearable payment devices shown above.



Q7 FC On a scale from 1 (strongly disagree) to 7 (strongly agree), please indicate how much you agree or disagree with the following statements about the wearable payment devices shown above.



Q8 TR On a scale from 1 (strongly disagree) to 7 (strongly agree), please indicate how much you agree or disagree with the following statements about this **new way of payment**.

	Strongly disagree	Neither agree nor disagree			Strongly agree		
	1	2	3	4	5	6	7
I trust that a transaction conducted through a wearable payment device is secure. ()				█			
I trust that payments made through wearable payment devices will be processed securely. ()				█			
I believe my personal information on wearable payment devices will be kept confidential. ()				█			
I believe that in case of any issue, the wearable payment service provider would intervene, investigate and defend my interests. ()				█			
I trust wearable payment devices to be reliable. ()				█			

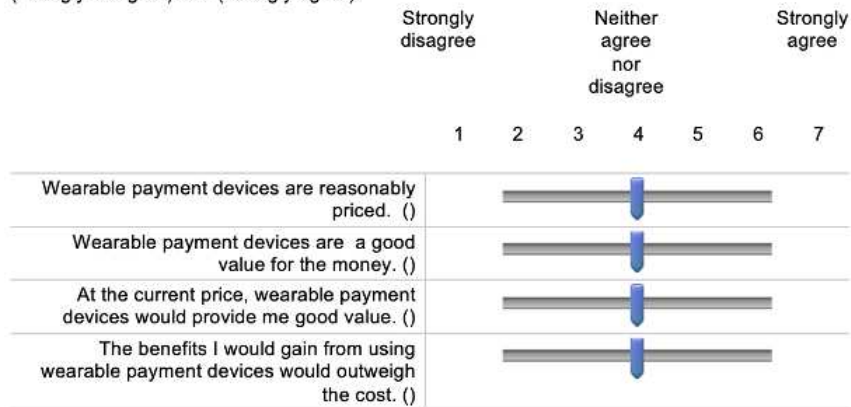
Page Break

Please take a moment to remind yourself of the wearable devices you saw. When answering this next section, think about the wearable payment devices **you would personally choose** or that **best represent your preferences**.

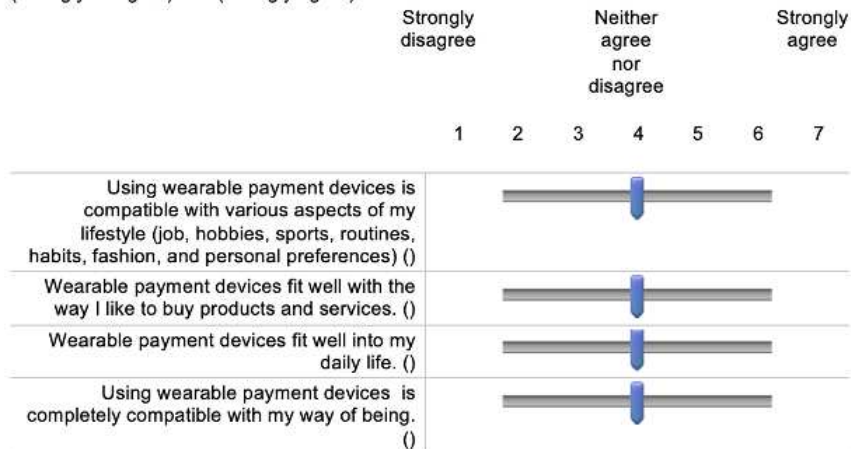
<p>MB WAY PULSE</p>  <p>14,99€ Silicone Water resistant</p>	<p>NEOS</p>  <p>59,99€ Leather strap Not water resistant</p>	<p>TAPSTER</p>  <p>39,95€ 59€ Leather 199€ Silver 69€ Leather Water resistant</p>
<p>TAP2</p>  <p>≈23€ Leather ≈64€ Ceramic ≈58€ Leather Water resistant</p>	<p>CNICK</p>  <p>119€ Zirconia Ceramic and 14k gold ring 1299€ Jet Stone Water resistant</p>	<p>PURE WRIST</p>  <p>≈21€ Silicone Water resistant</p>

Page Break

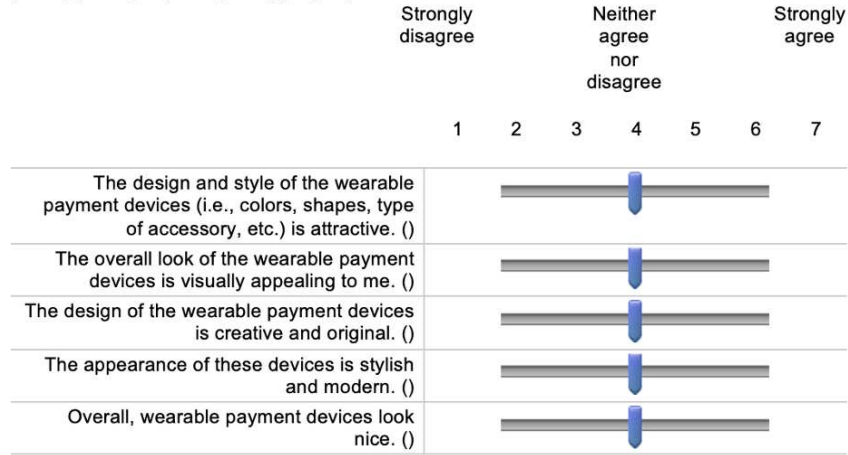
Q9 PV Rate how much you agree or disagree with the following statements on a scale from 1 (strongly disagree) to 7 (strongly agree).



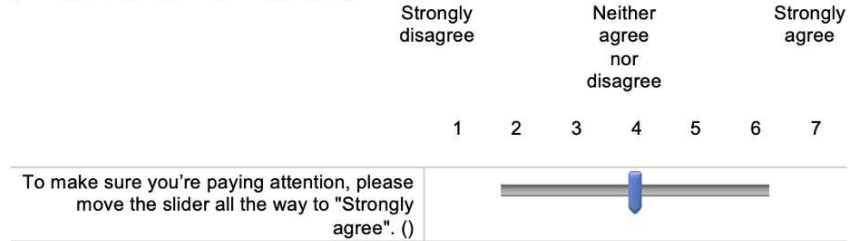
Q10 C Rate how much you agree or disagree with the following statements on a scale from 1 (strongly disagree) to 7 (strongly agree).



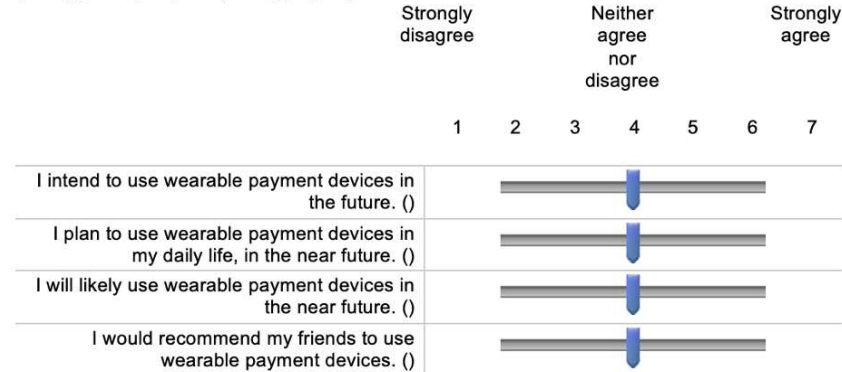
Q11 PA Rate how much you agree or disagree with the following statements on a scale from 1 (strongly disagree) to 7 (strongly agree).



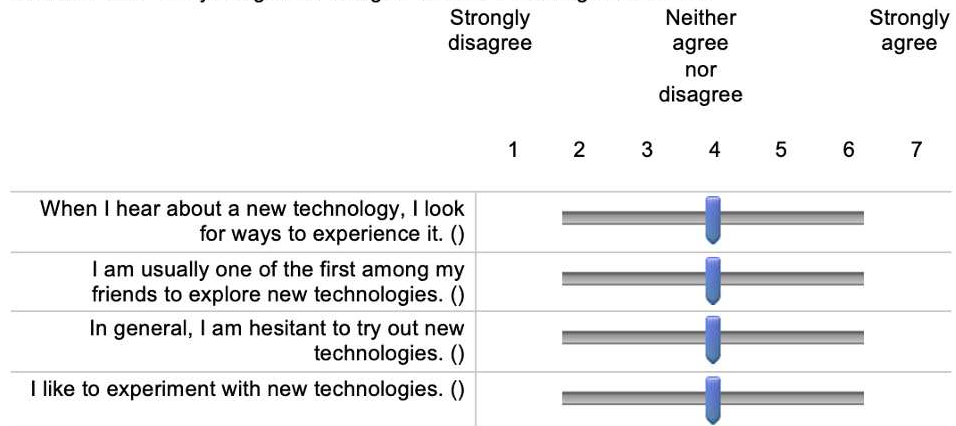
Q12 Rate how much you agree or disagree with the following statements on a scale from 1 (strongly disagree) to 7 (strongly agree).



Q13 BI Rate how much you agree or disagree with the following statements on a scale from 1 (strongly disagree) to 7 (strongly agree).



Q14 IN When answering this section, please think about **technologies in general** and your behavior towards them. On a scale from 1 (strongly disagree) to 7 (strongly agree), please indicate how much you agree or disagree with the following statements.



End of Block: Third Block: Perceptions | Terceiro Bloco: Percepções

Start of Block: Fourth Block: Demographic Information | Quarto Bloco: Informações Demográficas

We're almost there — this is the last section and the quickest one!

Q15 With which gender do you identify?

- Male (1)
- Female (2)
- Non-binary / third gender (3)
- Prefer not to say (4)

Q16 How old are you?

- 18 - 24 (1)
 - 25 - 34 (2)
 - 35 - 44 (3)
 - 45 - 54 (4)
 - 55 - 64 (5)
 - 65 - 74 (6)
 - 75 or older (7)
-

Q17 In which country do you currently reside?

▼ Afghanistan (1) ... Zimbabwe (1357)

Q18 What is your highest level of education completed?

- Primary Education (1)
 - High School (2)
 - Bachelor's Degree (3)
 - Master's Degree (4)
 - PhD or Doctorate (5)
 - Other (write below) (6) _____
-

Q19 What is your current employment status?

- Full-time employed (1)
- Part-time employed (2)
- Student (3)
- Working Student (4)
- Unemployed (5)
- Retired (6)
- Other (write below) (7) _____

End of Block: Fourth Block: Demographic Information | Quarto Bloco: Informações Demográficas

Appendix 2: Instrument Development

Construct	Code	Items	Sources
Performance Expectancy	PE	I believe that wearable payment devices would be useful in my daily life. Using wearable payment devices would help me accomplish payment tasks more quickly. I think using wearable payment devices would save me time. Wearable payment devices are useful for making payments. Using wearable payment devices would make it easier to make payments in my daily life. Using wearable payment devices would increase my efficiency when paying.	Venkatesh et al., 2012 Oliveira et al., 2016 Liébana-Cabanillas et al., 2018 Al Mamun et al., 2023 Chuah et al., 2016
Effort Expectancy	EE	Learning how to use wearable payment devices would be easy for me. I think interacting with wearable payment devices would be clear and understandable. I find wearable payment devices easy to use. I think I would be able to do the setup of the wearable payment devices. Payments done through wearable payment devices require minimum effort.	Venkatesh et al., 2012 Chuah et al., 2016 Liébana-Cabanillas et al., 2018
Social Influence	SI	If people who are important to me were using wearable payment devices, I would be more inclined to try it out. If people who influence my behavior recommended wearable payment devices, I would probably consider using it. If people whose opinions I value showed interest in wearable payment devices, I would be more willing to explore it. If my friends started using wearable payment devices, I would feel more motivated to try it myself.	Venkatesh et al., 2012
Facilitating Conditions	FC	Wearable payment devices are compatible with other technologies I use (for example, smartphone, payment terminals). If I had difficulties with setting up or using wearable payment devices I believe I could easily get assistance from a support team. (Deleted item) I have the financial resources required to use wearable payment devices (funds to buy and use). I have the resources necessary to use wearable payment devices (mobile phone, Internet).	Venkatesh et al., 2012 Al Mamun et al., 2023
Trust	TR	I trust that a transaction conducted through a wearable payment device is secure. I trust that payments made through wearable payment devices will be processed securely. I believe my personal information on wearable payment devices will be kept confidential. I believe that in case of any issue, the wearable payment service provider would intervene, investigate and defend my interests. I trust wearable payment devices to be reliable.	Al Mamun et al., 2023 Slade et al., 2023
Price Value	PV	Wearable payment devices are reasonably priced. Wearable payment devices are a good value for the money. At the current price, wearable payment devices would provide me good value. The benefits I would gain from using wearable payment devices would outweigh the cost.	Venkatesh et al., 2012
Compatibility	CM	Using wearable payment devices is compatible with various aspects of my lifestyle (job, hobbies, sports, routines, habits, fashion, and personal preferences). Wearable payment devices fit well with the way I like to buy products and services. Wearable payment devices fit well into my daily life. Using wearable payment devices is completely compatible with my way of being.	Oliveira et al., 2016 Yang et al., 2016 Liébana-Cabanillas et al., 2018
Perceived Aesthetics	PA	The design and style of the wearable payment devices (i.e., colors, shapes, type of accessory, etc.) is attractive. The overall look of the wearable payment devices is visually appealing to me. The design of the wearable payment devices is creative and original. The appearance of these devices is stylish and modern. Overall, wearable payment devices look nice.	Yang et al., 2016
Behavioral Intention	BI	I intend to use wearable payment devices in the future. I plan to use wearable payment devices in my daily life, in the near future. I will likely use wearable payment devices in the near future. I would recommend my friends to use wearable payment devices.	Venkatesh et al., 2012 Oliveira et al., 2016 Liébana-Cabanillas et al., 2018
Innovativeness	IN	When I hear about a new technology, I look for ways to experience it. I am usually one of the first among my friends to explore new technologies. (Deleted item) In general I am hesitant to try out new technologies. (Deleted item) I like to experiment with new technologies.	Oliveira et al., 2016 Liébana-Cabanillas et al., 2018

Appendix 3: Mahalanobis distance

MAH_1	Prob_MAH
48.00716	.0000
38.48042	.0000
36.40886	.0001
35.67149	.0001
33.74186	.0002
31.38732	.0005
28.09804	.0017
27.66381	.0020
25.84535	.0040
25.47595	.0045
24.89561	.0055

Appendix 4: Descriptive Statistics

Table 4.1: Gender

Gender		
	N	%
Male	99	39.0%
Female	153	60.2%
Prefer not to say	2	0.8%

Table 4.2: Age

Age		
	N	%
18 - 24	123	48.4%
25 - 34	28	11.0%
35 - 44	22	8.7%
45 - 54	50	19.7%
55 - 64	28	11.0%
65 - 74	2	0.8%
75 or older	1	0.4%

Table 4.3: Current Residence

Current Residence		
	N	%
Argentina	1	0.4%
Brazil	3	1.2%
Canada	2	0.8%
Denmark	1	0.4%
France	1	0.4%
Germany	23	9.1%
Italy	2	0.8%
Portugal	205	80.7%
Spain	1	0.4%
Switzerland	1	0.4%
United Kingdom of Great Britain and Northern Ireland	8	3.1%
United States of America	6	2.4%

Table 4.4: Level of Education

Level of Education		
	N	%
High School	48	18.9%
Bachelor's Degree	129	50.8%
Master's Degree	65	25.6%
PhD or Doctorate	4	1.6%
Other (write below)	8	3.1%

Table 4.5: Employment Status

Employment Status		
	N	%
Full-time employed	135	53.1%
Part-time employed	17	6.7%
Student	62	24.4%
Working Student	18	7.1%
Unemployed	6	2.4%
Retired	2	0.8%
Other (write below)	14	5.5%

Table 4.6: Construct Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
Performance Expectancy	254	1.00	7.00	5.2316	1.53335
Effort Expectancy	254	2.00	7.00	6.1748	.89601
Social Influence	254	1.00	7.00	4.7844	1.63038
Facilitating Conditions	254	2.00	7.00	6.0341	1.00751
Trust	254	1.00	7.00	4.5953	1.51961
Price Value	254	1.00	7.00	4.2579	1.43104
Compatibility	254	1.00	7.00	4.8130	1.68608
Perceived Aesthetics	254	1.00	7.00	4.4417	1.64530
Behavioral Intention	254	1.00	7.00	3.9281	1.86355
Innovativeness	254	1.00	7.00	4.7231	1.44611
Valid N (listwise)	254				

Appendix 5: Reliability Analysis - Cronbach's Alpha

	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted	Cronbach's Alpha	Qualitative
Performance Expectancy (6 items)			.949	Very good
I believe that wearable payment devices would be useful in my daily life.	.800	.944		
Using wearable payment devices would help me accomplish payment tasks more quickly.	.847	.939		
I think using wearable payment devices would save me time.	.862	.937		
Wearable payment devices are useful for making payments.	.823	.942		
Using wearable payment devices would make it easier to make payments in my daily life.	.900	.932		
Using wearable payment devices would increase my efficiency when paying.	.833	.941		
Effort Expectancy (5 items)			.876	Good
Learning how to use wearable payment devices would be easy for me.	.706	.852		
I think interacting with wearable payment devices would be clear and understandable.	.752	.838		
I find wearable payment devices easy to use.	.734	.842		
I think I would be able to do the set up of the wearable payment devices.	.682	.857		
Payments done through wearable payment devices require minimum effort.	.672	.857		
Social Influence (4 items)			.959	Very good
If people who are important to me were using wearable payment devices, I would be more inclined to try it out.	.890	.948		
If people who influence my behavior recommended wearable payment devices, I would probably consider using it.	.918	.940		
If people whose opinions I value showed interest in wearable payment devices, I would be more willing to explore it.	.921	.939		
If my friends started using wearable payment devices, I would feel more motivated to try it myself.	.865	.956		
Facilitatins Conditions (3 items) - Final			.699	Reasonable
Wearable payment devices are compatible with other technologies I use (for example, smartphone, payment terminals).	.558	.564		
I have the financial resources required to use wearable payment devices (funds to buy and use).	.487	.696		
I have the resources necessary to use wearable payment devices (mobile phone, Internet).	.553	.584		
Facilitating Conditions (4 items) - Initial			.676	Weak
Wearable payment devices are compatible with other technologies I use (for example, smartphone, payment terminals).	.568	.553		
If I had difficulties with setting up or using wearable payment devices I believe I could easily get assistance from a support team. (Deleted item)	.336	.699		
I have the financial resources required to use wearable payment devices (funds to buy and use).	.514	.575		
I have the resources necessary to use wearable payment devices (mobile phone, Internet).	.474	.609		
Trust (5 items)			.923	Very good
I trust that a transaction conducted through a wearable payment device is secure.	.830	.899		
I trust that payments made through wearable payment devices will be processed securely.	.807	.904		
I believe my personal information on wearable payment devices will be kept confidential.	.785	.908		
I believe that in case of any issue, the wearable payment service provider would intervene, investigate and defend my interests.	.723	.921		
I trust wearable payment devices to be reliable.	.857	.893		
Price Value (4 items)			.925	Very good
Wearable payment devices are reasonably priced.	.774	.921		
Wearable payment devices are a good value for the money.	.876	.888		
At the current price, wearable payment devices would provide me good value.	.902	.876		
The benefits I would gain from using wearable payment devices would outweigh the cost.	.779	.923		

Compatibility (4 items)			.945	Very good
Using wearable payment devices is compatible with various aspects of my lifestyle (job, hobbies, sports, routines, habits, fashion, and personal preferences).	.841	.936		
Wearable payment devices fit well with the way I like to buy products and services.	.873	.926		
Wearable payment devices fit well into my daily life.	.922	.911		
Using wearable payment devices is completely compatible with my way of being.	.838	.938		
Perceived Aesthetics (5 items)			.956	Very good
The design and style of the wearable payment devices (i.e., colors, shapes, type of accessory, etc.) is attractive.	.882	.944		
The overall look of the wearable payment devices is visually appealing to me.	.876	.945		
The design of the wearable payment devices is creative and original.	.841	.951		
The appearance of these devices is stylish and modern.	.886	.944		
Overall, wearable payment devices look nice.	.900	.941		
Behavioral Intention (4 items)			.967	Very good
I intend to use wearable payment devices in the future.	.919	.957		
I plan to use wearable payment devices in my daily life, in the near future.	.947	.949		
I will likely use wearable payment devices in the near future.	.942	.950		
I would recommend my friends to use wearable payment devices.	.867	.972		
Innovativeness (3 items) - Final			.855	Good
When I hear about a new technology, I look for ways to experience it.	.746	.783		
I am usually one of the first among my friends to explore new technologies.	.738	.791		
I like to experiment with new technologies.	.706	.816		
Innovativeness (4 items)			.737	Reasonable
When I hear about a new technology, I look for ways to experience it.	.667	.604		
I am usually one of the first among my friends to explore new technologies.	.628	.616		
In general I am hesitant to try out new technologies. (Deleted item)	.227	.855		
I like to experiment with new technologies.	.688	.592		

Appendix 6: Normality Assessment

Tests of Normality

	Kolmogorov-Smirnov ^a			Descriptives	
	Statistic	df	Sig.	Skewness	Kurtosis
Performance Expectancy	,124	254	<,001	-,839	,047
Effort Expectancy	,179	254	<,001	-1,295	2,029
Social Influence	,120	254	<,001	-,605	-,461
Facilitating Conditions	,169	254	<,001	-1,415	2,348
Trust	,082	254	<,001	-,279	-,482
Price Value	,058	254	,037	-,100	-,556
Compatibility	,105	254	<,001	-,557	-,592
Perceived Aesthetics	,082	254	<,001	-,301	-,826
Behavioral Intention	,090	254	<,001	,001	-1,124
Innovativeness	,089	254	<,001	-,357	-,630

a. Lilliefors Significance Correction

Appendix 7: Correlation Analysis

		Correlations									
		Behavioral Intention	Performance Expectancy	Effort Expectancy	Social Influence	Facilitating Conditions	Trust	Price Value	Compatibility	Perceived Aesthetics	Innovativeness
Behavioral Intention	Pearson Correlation	1	,667**	,183**	,586**	,308**	,575**	,702**	,779**	,655**	,496**
	Sig. (2-tailed)		<,001	,003	<,001	<,001	<,001	<,001	<,001	<,001	<,001
	N	254	254	254	254	254	254	254	254	254	254
Performance Expectancy	Pearson Correlation	,667**	1	,250**	,568**	,249**	,495**	,563**	,715**	,483**	,353**
	Sig. (2-tailed)	<,001		<,001	<,001	<,001	<,001	<,001	<,001	<,001	<,001
	N	254	254	254	254	254	254	254	254	254	254
Effort Expectancy	Pearson Correlation	,183**	,250**	1	,168**	,594**	,367**	,135*	,294**	,067	,442**
	Sig. (2-tailed)	,003	<,001		,007	<,001	<,001	,031	<,001	,284	<,001
	N	254	254	254	254	254	254	254	254	254	254
Social Influence	Pearson Correlation	,586**	,568**	,168**	1	,228**	,539**	,514**	,627**	,388**	,345**
	Sig. (2-tailed)	<,001	<,001	,007		<,001	<,001	<,001	<,001	<,001	<,001
	N	254	254	254	254	254	254	254	254	254	254
Facilitating Conditions	Pearson Correlation	,308**	,249**	,594**	,228**	1	,335**	,240**	,361**	,148*	,457**
	Sig. (2-tailed)	<,001	<,001	<,001	<,001		<,001	<,001	<,001	,018	<,001
	N	254	254	254	254	254	254	254	254	254	254
Trust	Pearson Correlation	,575**	,495**	,367**	,539**	,335**	1	,566**	,648**	,451**	,438**
	Sig. (2-tailed)	<,001	<,001	<,001	<,001	<,001		<,001	<,001	<,001	<,001
	N	254	254	254	254	254	254	254	254	254	254
Price Value	Pearson Correlation	,702**	,563**	,135*	,514**	,240**	,566**	1	,702**	,630**	,308**
	Sig. (2-tailed)	<,001	<,001	,031	<,001	<,001	<,001		<,001	<,001	<,001
	N	254	254	254	254	254	254	254	254	254	254
Compatibility	Pearson Correlation	,779**	,715**	,294**	,627**	,361**	,648**	,702**	1	,617**	,494**
	Sig. (2-tailed)	<,001	<,001	<,001	<,001	<,001	<,001	<,001		<,001	<,001
	N	254	254	254	254	254	254	254	254	254	254
Perceived Aesthetics	Pearson Correlation	,655**	,483**	,067	,388**	,148*	,451**	,630**	,617**	1	,315**
	Sig. (2-tailed)	<,001	<,001	,284	<,001	,018	<,001	<,001	<,001		<,001
	N	254	254	254	254	254	254	254	254	254	254
Innovativeness	Pearson Correlation	,496**	,353**	,442**	,345**	,457**	,438**	,308**	,494**	,315**	1
	Sig. (2-tailed)	<,001	<,001	<,001	<,001	<,001	<,001	<,001	<,001	<,001	
	N	254	254	254	254	254	254	254	254	254	254

** . Correlation is significant at the 0.01 level (2-tailed).

* . Correlation is significant at the 0.05 level (2-tailed).

Appendix 8: Multiple Linear Regression Analysis

Model Summary^b

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,840 ^a	,706	,696	1,02682	1,830

a. Predictors: (Constant), Perceived Aesthetics, Effort Expectancy, Social Influence, Facilitating Conditions, Performance Expectancy, Trust, Price Value, Compatibility

b. Dependent Variable: Behavioral Intention

Error's independence Durbin-Watson $2 \pm 0,5$. DW=1,830

ANOVA^a

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	620,309	8	77,539	73,541	<,001 ^b
	Residual	258,317	245	1,054		
	Total	878,626	253			

a. Dependent Variable: Behavioral Intention

b. Predictors: (Constant), Perceived Aesthetics, Effort Expectancy, Social Influence, Facilitating Conditions, Performance Expectancy, Trust, Price Value, Compatibility

Coefficients^a

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	-1,622	,519		-3,125	,002		
	Performance Expectancy	,204	,062	,167	3,259	,001	,454	2,201
	Effort Expectancy	-,152	,094	-,073	-1,609	,109	,584	1,713
	Social Influence	,109	,054	,095	2,024	,044	,541	1,848
	Facilitating Conditions	,165	,082	,089	2,002	,046	,604	1,656
	Trust	,055	,061	,045	,911	,363	,489	2,044
	Price Value	,225	,070	,173	3,220	,001	,416	2,406
	Compatibility	,342	,074	,309	4,634	<,001	,270	3,706
	Perceived Aesthetics	,236	,054	,208	4,367	<,001	,528	1,894

a. Dependent Variable: Behavioral Intention

Casewise Diagnostics^a

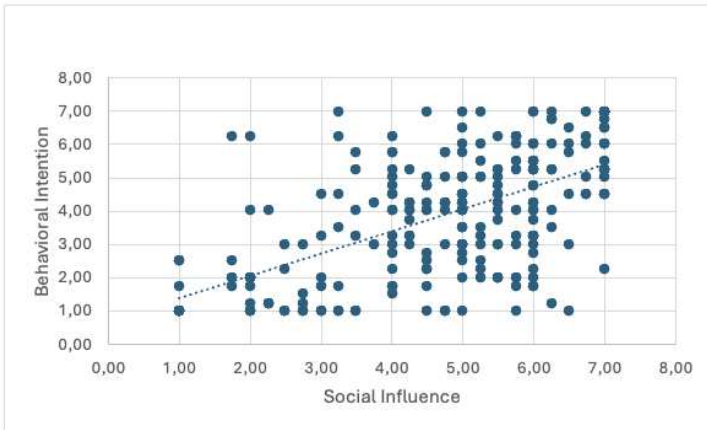
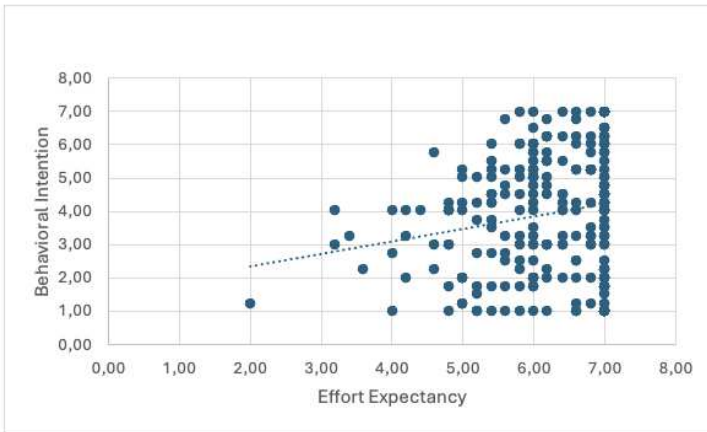
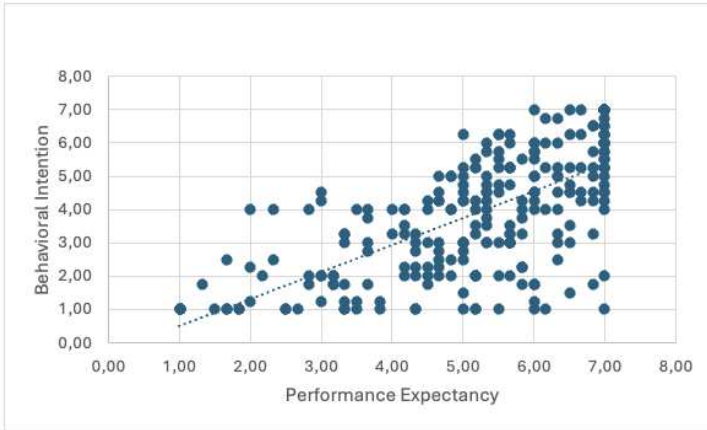
Case Number	Std. Residual	Behavioral Intention	Predicted Value	Residual
1	3,137	7,00	3,7793	3,22074

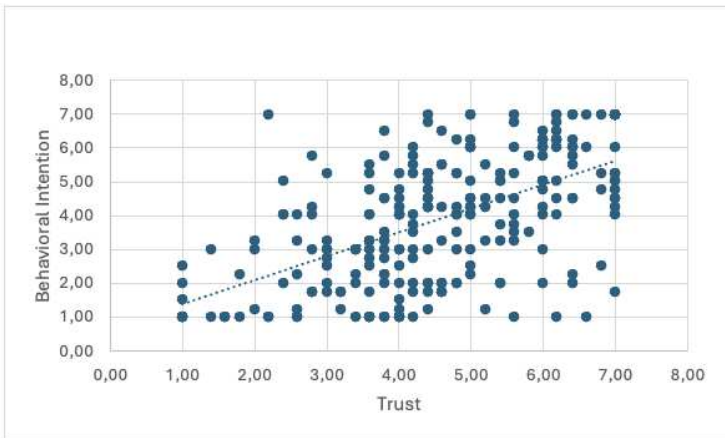
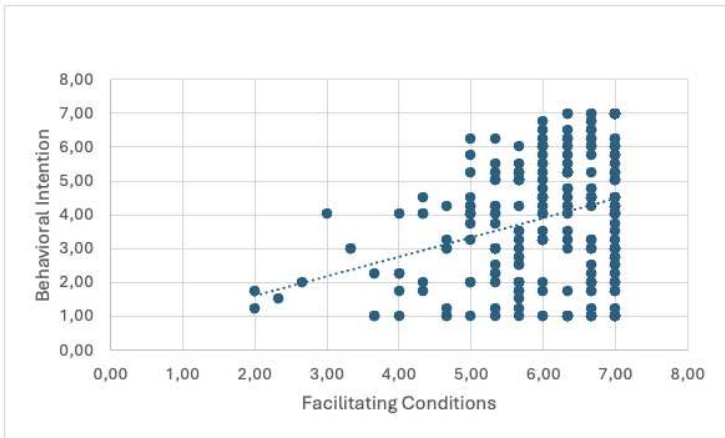
a. Dependent Variable: Behavioral Intention

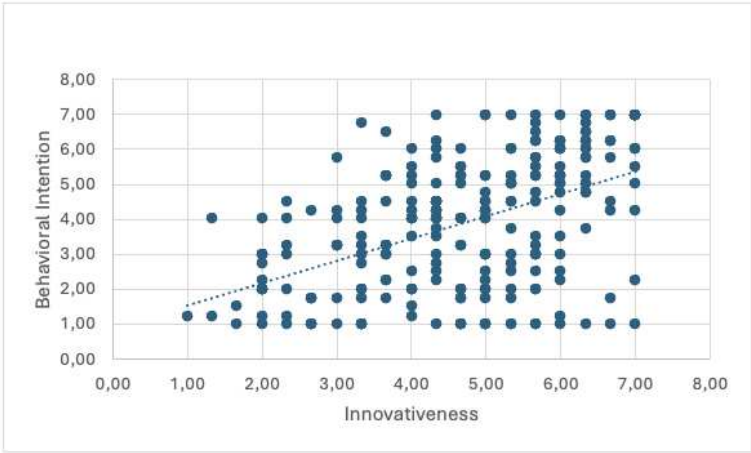
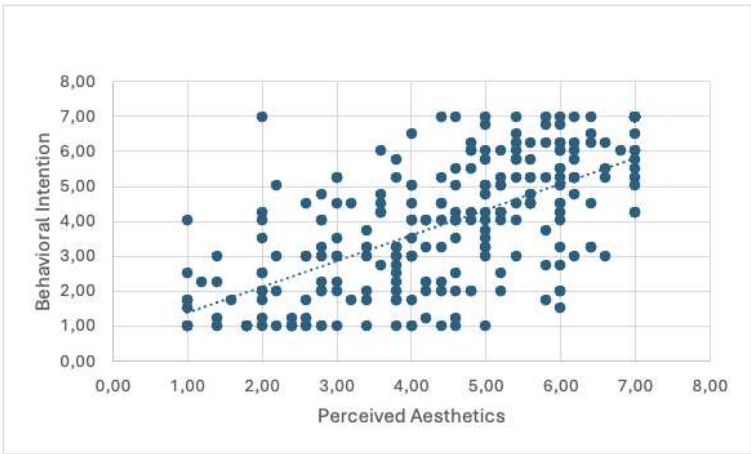
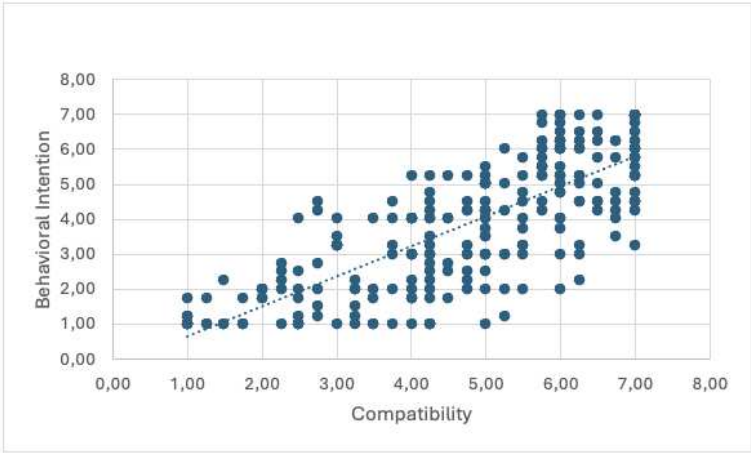
Residuals Statistics^a

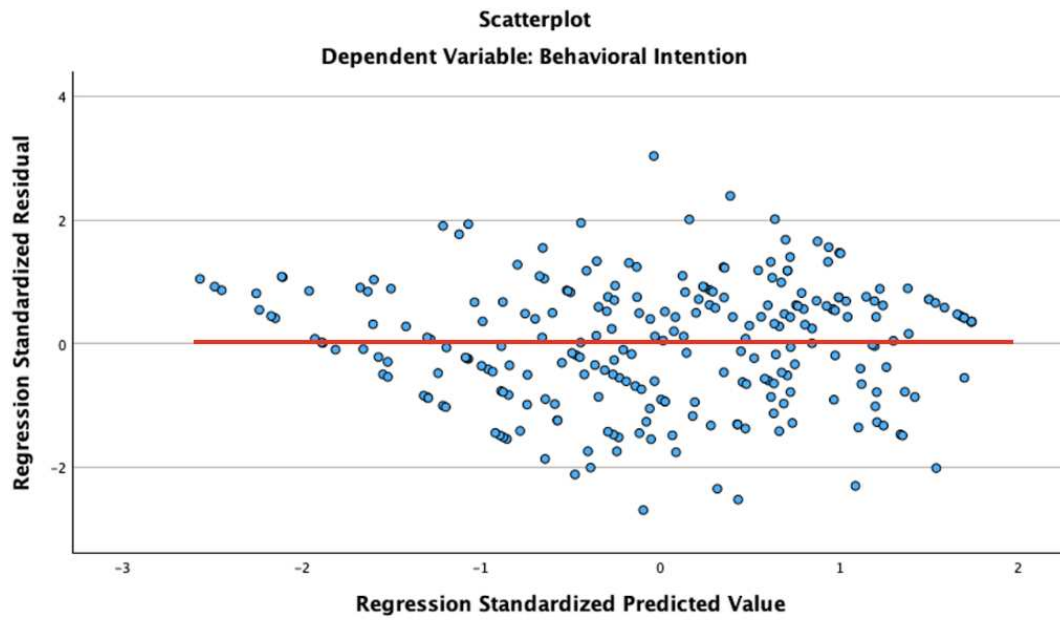
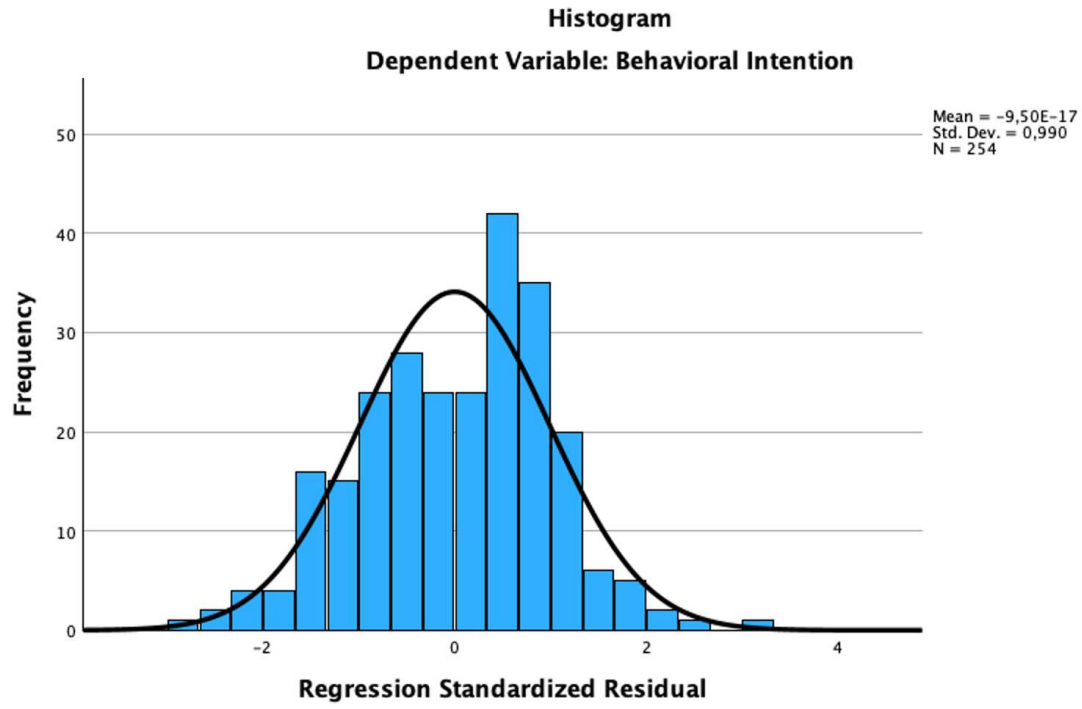
	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	-,0767	6,6650	3,9281	1,56583	254
Residual	-2,67485	3,22074	,00000	1,01045	254
Std. Predicted Value	-2,558	1,748	,000	1,000	254
Std. Residual	-2,605	3,137	,000	,984	254

a. Dependent Variable: Behavioral Intention









Appendix 9: Moderator Analysis

Figure 9.1. Impact of IN on the relationship between PE and BI

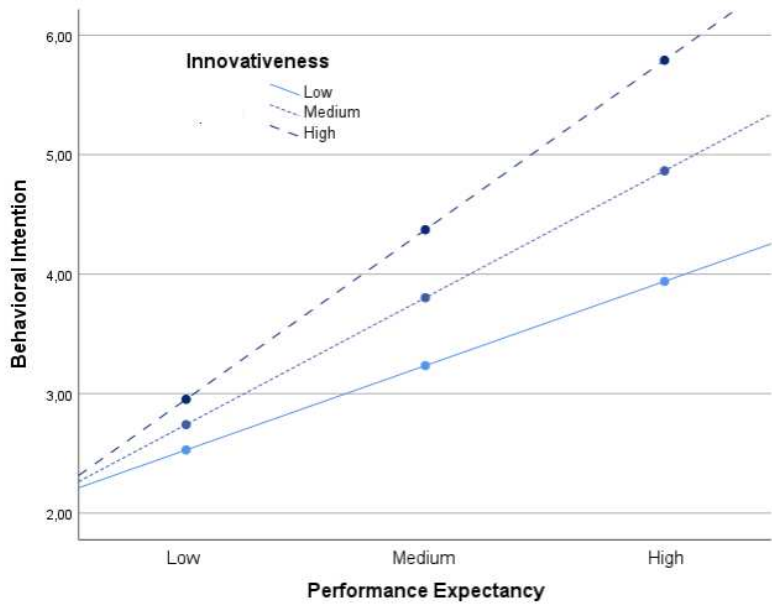


Figure 9.2. Impact of IN on the relationship between EE and BI

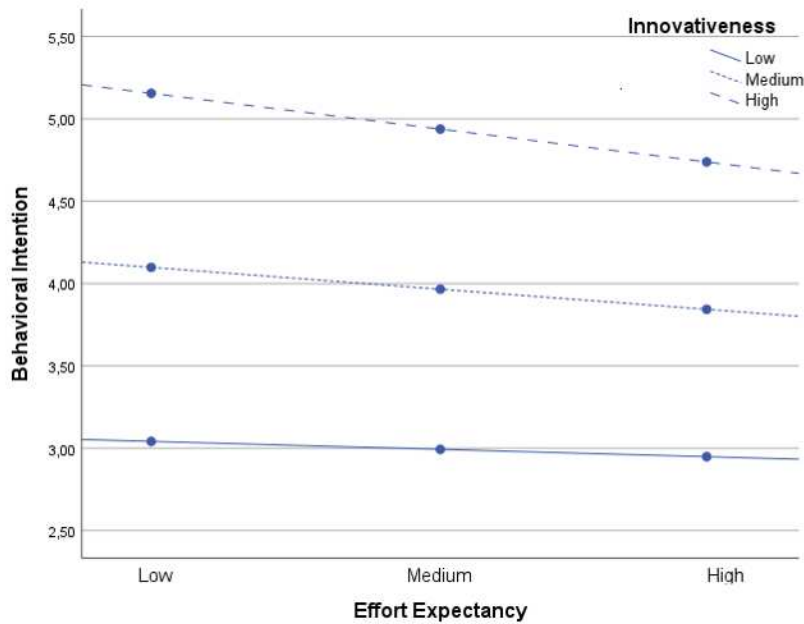


Figure 9.3. Impact of IN on the relationship between CM and BI

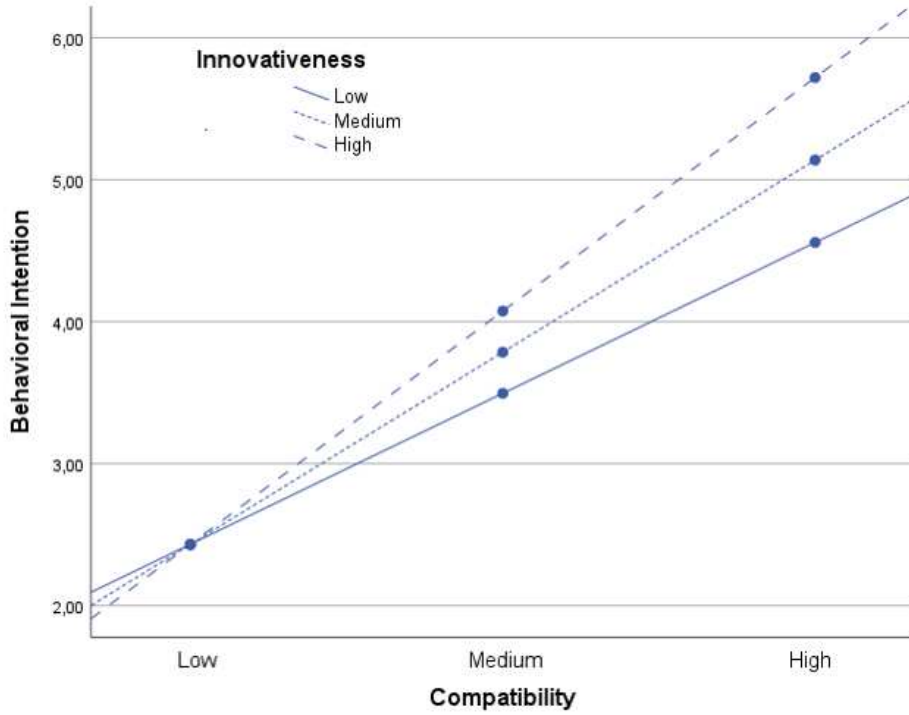


Figure 9.4. Impact of IN on the relationship between FC and BI

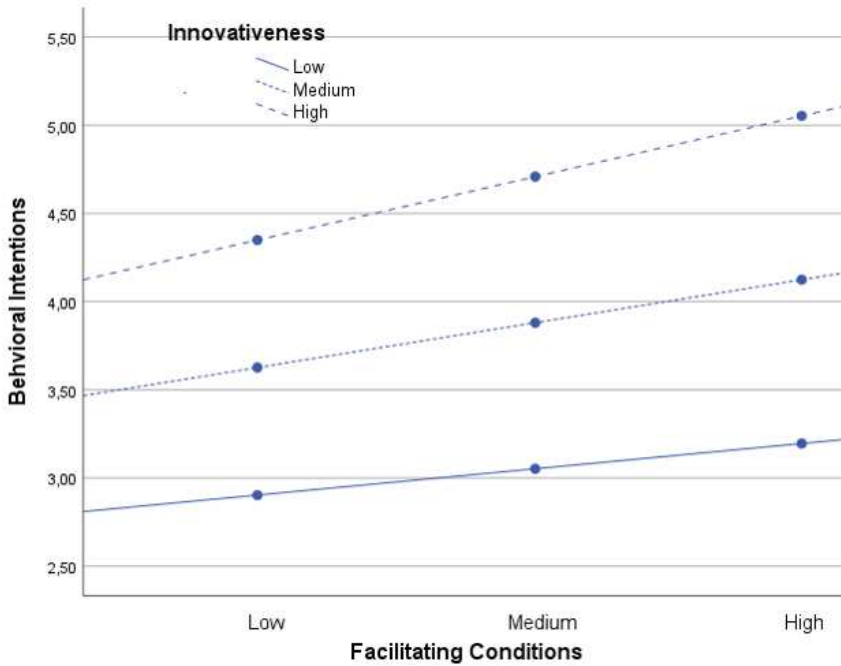


Figure 9.5. Impact of IN on the relationship between TR and BI

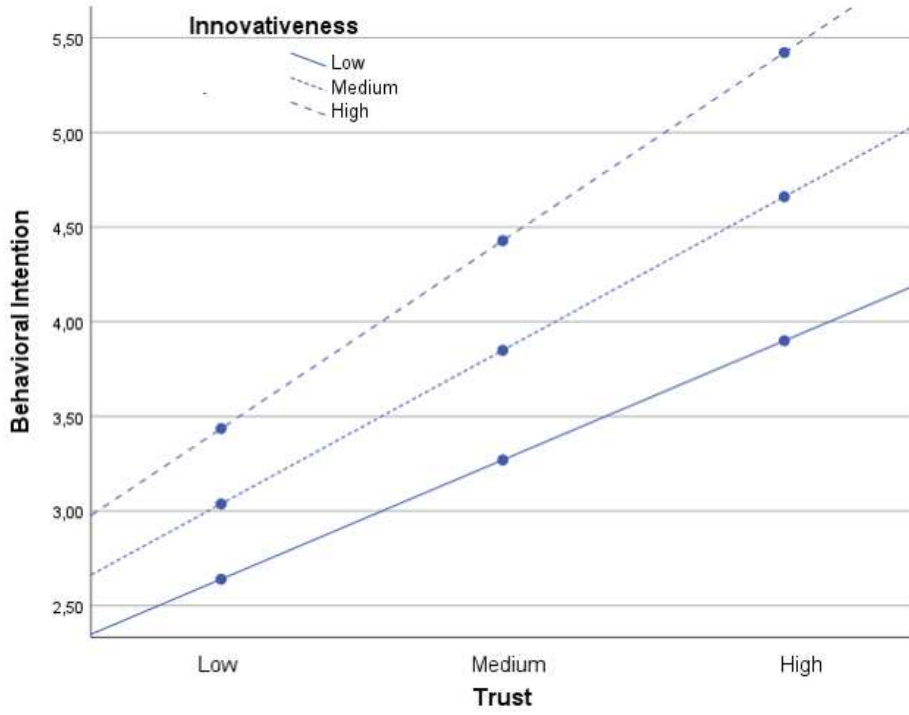


Figure 9.6. Impact of IN on the relationship between SI and BI

