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Navigating the Privacy–Personalization Paradox: Understanding User Adoption of AI-Powered Fitness Apps

Master Thesis

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Abstract

This study explores how AI-driven service personalization and privacy concerns influence the adoption of AI-powered fitness applications. While users appreciate the benefits of tailored fitness recommendations, they simultaneously express concerns about the privacy of their personal data. This creates a privacy-personalization paradox, which is an important issue in the context of AI-powered fitness apps, since they use sensitive data to create personalized content. The hypothesized model is tested through a hierarchical regression analysis, using research data from 103 valid survey responses. The findings reveal that personalization positively affects the intention to adopt AI-powered fitness apps, while privacy concerns have a negative effect, both in line with previous research. Surprisingly, privacy concerns did not moderate the relationship between personalization and adoption, which suggests that privacy concerns and personalization do not interact, but operate as independent forces on adoption intention. The study contributes to AI adoption literature by highlighting the nuanced and independent roles of personalization and privacy concerns in shaping user behavior regarding AI-powered fitness apps. The study also provides directions for future research, and practical insights for app developers and fitness tech companies, and personal trainers.

Keywords: Artificial intelligence (AI), Technology adoption, Privacy-Personalization Paradox, Fitness applications, Privacy concerns, Service Personalization

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1. Introduction

Artificial intelligence (AI) is increasingly being integrated into the fitness industry, driven by demand for personalized, data-driven fitness solutions (Chin et al., 2022). One of the most significant applications of AI in fitness is the creation of personalized workout plans (Vioreanu, 2024). AI algorithms analyse user's data, like age, weight, gender, fitness level, and goals, to develop tailored exercise routines that optimize fitness results. These systems also provide insights that help prevent overtraining and injuries, enhancing the overall effectiveness of fitness routines (Farrokhi et al., 2021). However, as AI-driven customization improves fitness experiences, it simultaneously raises concerns about data privacy and security (Rahman et al., 2023).

Current research found that consumers are often willing to share personal data in exchange for better recommendations and improved user experiences (Nama, 2021). However, heightened privacy concerns may lead to resistance or limited data sharing, which can negatively impact adoption rates (Beldad et al., 2011). In the context of technology adoption, this is referred to as the *Privacy-personalization paradox*. While users benefit from AI-driven customization, they also face potential privacy risks, creating a trade-off between enhanced personalization and data security concerns (Awad & Krishnan, 2006). This paradox is especially relevant for AI-powered fitness applications, as these apps rely on collecting and analysing highly sensitive personal data, such as heart rate, sleep patterns, body composition, location, and personal fitness metrics (Peart et al., 2017). The definitions and central concepts within this research will be discussed in detail in Chapter 2.

This research specifically examines the tension between privacy concerns and AI-driven service personalization and how they together influence the intention to adopt AI-powered fitness applications. It aims to answer the central research question: "*How do privacy concerns and AI-driven service personalization influence users' intention to adopt AI-powered fitness applications?*".

This research is scientifically relevant because it addresses the significant gap in current AI adoption literature by explicitly examining the privacy-personalization paradox in the context of AI-powered fitness apps. As the amount of literature on AI adoption in domains such as social media (Cloarec et al., 2024; Kawaf et al., 2023), tourism (Lei et al., 2022; Morosan & DeFranco, 2016), and smart home services (Zhang et al., 2022) is growing, there is little research available that explores how the privacy-personalization trade-off specifically influences the adoption of AI-integrated fitness applications (Chin et al., 2022). Given the personal and sensitive nature of fitness apps, understanding this trade-off is very important. This research contributes to a more nuanced understanding of AI adoption in digital health contexts, where highly sensitive data is central to user experience.

Considering the practical relevance, this research will generate valuable insights for fitness technology companies, app developers, and personal trainers. Recognizing this privacy-personalisation paradox in fitness apps leads to a better understanding of the adoption of AI-powered fitness apps. This helps businesses enhance user experience, improve data security measures, and develop more user-friendly fitness applications (Ioannidou & Sklavos, 2021). Next to that, individuals and personal trainers can use AI tools to create more effective and personalized fitness plans and increasing client satisfaction. By balancing privacy protection and optimizing service personalization, the sports and fitness industry can encourage sustainable growth of AI-powered fitness solutions.

This research consists of three parts. The first part, chapters 2 and 3, are conceptual in nature. Chapter 2, the theoretical background, indicates what the central concepts are and how they relate to each other. Chapter 3 describes how data are collected in order to answer the research question and the underlying relations. The second part of this research, chapters 4, 5, and 6 (respectively Results, Discussion, and Conclusion), discusses the specific results of this research and implications for practice. Limitations of this study and possibilities for future research will be discussed will be discussed in the last part of this research.

2. Theoretical Background

2.1 Literature review

AI-powered fitness apps are application systems that integrates sports, leisure and social interaction and can provide users with certain functions to achieve their expected health or fitness goals (J. Lee & Lin, 2023). They serve as a useful resource for providing individuals with physical exercise guidelines (Molina & Myrick, 2020). AI-powered fitness apps use artificial intelligence to create personalized workout plans based on the user's needs and preferences, track progress by collecting data from sensors or manual input, and provide real-time feedback and recommendations (Kidecha, 2025). These apps continuously adapt to the user's progress, ensuring that the fitness recommendations perfectly align with the user's needs and goals (Kuru, 2023). Compared with 'general' non-AI fitness apps, AI-powered Fitness Apps aim to deliver more intelligent and personalized fitness services to users engaging in physical activities and exercise (J. Lee & Lin, 2023).

As AI continues to revolutionize fitness apps, it transforms them into smarter, more interactive programs that offer users a more personal experience. However, this rapid evolution brings new challenges, including the need to balance this high-level personalization with ethical (privacy-related) considerations (Dhirani et al., 2023). While users appreciate the benefits of personalized and tailored AI-driven experiences, they simultaneously express concerns about data security and privacy (Awad & Krishnan, 2006). Guo et al. (2015) also found that consumers want to utilize personalized services, but they are hesitant to share personal information due to privacy concerns. In academic literature, this phenomenon is referred to as the *privacy-personalization paradox*.

Despite a considerable amount of academic literature on AI adoption, there remains a gap in research on the personalization–privacy paradox (Shi et al., 2023). This paradox has been examined in multiple contexts, such as hospitality (Lei et al., 2022; Morosan & DeFranco, 2016), smart home services and IOT (Zhang et al., 2022; A. Lee, 2021), e-commerce (Aguirre et al., 2016; Lavado-Nalvaiz et al., 2022) and social media (Cloarec et al., 2024; Kawaf et al., 2023). The above studies have investigated the privacy-personalization paradox in technology adoption in different domains, but there is little academic research available on the personalization–privacy paradox in the context of AI-powered fitness apps. Because personalization and privacy are important determinants of whether AI is to be implemented in a sensitive context (Guo et al., 2015), the impact of AI-driven service personalization and privacy concerns on user adoption of AI-powered fitness apps deserves further exploration.

2.2 AI-driven Service Personalization

Based on Liu and Tao (2021), AI-driven Service Personalization, in this study, refers to the degree to which AI-powered fitness apps can provide specific workout recommendations, based on users' personal fitness data and behavior. This means that the app recognizes and incorporates the user's personal fitness goals, preferences, and constraints , such as desired workout intensity, available time, or dietary habits (Kuru, 2023). The system then uses this information to generate tailored workout plans, exercise recommendations, or nutrition guidance (Bhandari et al., 2025). AI techniques such as machine learning algorithms and natural language processing are often used in these apps to analyse such user data (J. Lee & Lin, 2023).

A high level of personalization is achieved when the provided content by the app closely aligns with the user's actual fitness strategy (Chin et al., 2022). For example, the algorithm can personalize recommendations for users with different fitness levels, such as beginners who might need more gradual progressions or advanced athletes who desire high-intensity workouts. Similarly, different recommendations can be given based on age, such as exercises that are tailored for older adults (e.g. focusing on joint stability and flexibility), or for younger users aiming to build strength and endurance. Also, personalization could be based on specific fitness goals, such as weight loss, muscle gain or improving cardiovascular health. Tailoring content and recommendations to individual preferences and broader contextual factors, makes the app more relevant for a specific user, thereby increasing the personalization aspect.

C. Wang & Qi (2021) concluded that personalization is a critical component to enhance the attractiveness and acceptability of mHealth apps. Similarly, Farrokhi et al. (2021) found that AI-driven personalization, leveraging personal metrics like heart rate, activity level, and fitness goals, enhances user experiences and motivation, thereby increasing adoption rates. The Task-Technology Fit (TTF) model (Goodhue & Thompson, 1995) poses that technology is more likely to have a significant positive impact on performance if the capabilities fit well with the tasks of the user. Personalization is aimed to improve the alignment of the app's functions with the individual user's specific health goals, thereby effectively improving the fit. This improved fit means that the user can better accomplish their tasks (e.g. sticking to a training schedule) which enhances their perceived usefulness of the app, thereby increasing adoption rates.

According to several studies utilizing the Technology Acceptance Model (TAM) (Davis, 1989), personalization leads to higher degrees of perceived usefulness, by tailoring the system or service to the individual's preferences, needs, and behaviors, which will in turn positively affect the intention to adopt and use such services (Chin et al., 2022; Zhang et al., 2014). According to the Unified Theory of Acceptance and Use of Technology (UTAUT), as proposed by Venkatesh et al. (2003), personalization positively influences key determinants of technology adoption. Also, personalization impacts user trust, which is crucial for adoption. K. Wu et al. (2011) argue that personalized systems can create greater trust between users and the technology, which increases user acceptance. When users believe that a system understands their needs, they are more likely to adopt it.

Grounded in academic literature, and using the logic of TTF, TAM, UTAUT, this research proposes that AI-driven Service Personalization positively affects the Intention to Adopt AI-powered fitness apps.

H1: AI-driven service personalization has a positive effect on the intention to adopt AI-powered fitness apps.

2.3 Privacy Concerns

Dhagarra et al. (2020) define Privacy Concerns as "Concerns for loss of privacy and need for protection against uncalled-for communication and misuse of personal information" in the context of mHealth services. Like mHealth apps, AI-powered fitness applications collect and process sensitive personal data, including biometrics, activity levels, and behavioral patterns. Therefore, this research will use the same definition, however the measurement-items will be slightly adapted in order to fit the context of AI-powered fitness applications.

To provide the personalized content (e.g., adaptive workout plans, real-time coaching, and tailored health recommendations), AI powered fitness apps rely on personalization, which requires that consumers share their health information (e.g., age, weight, fitness level, heart rate, sleep patterns, and dietary habits). The challenge lies in the tension between the benefits of personalization and the (perceived) costs of disclosing sensitive data. As noted by Awad and Krishnan (2006), consumers face this *privacy-personalization paradox*. This paradox is particularly relevant to AI-driven services in health and fitness, where the personalization of workout recommendations is directly tied to the sharing of sensitive data.

Moreover, the integration of AI technologies like Large Language Models (LLMs) and machine learning algorithms have increased the capabilities to not only collect users' data, but also to analyse and profile it in real-time (Njiru et al., 2025). These advancements have enabled the production of highly personalized services, but they also increasingly heighten privacy concerns as users realize their data can be continuously monitored (Zhang & Dafoe, 2019). The core issue lies in the fact that, while consumers may be willing to share some personal information for the benefits of personalization, this willingness decreases if they perceive that the loss of privacy outweighs the value they gain from the services (Sheng et al., 2008). This phenomenon is also reflected in privacy calculus theory (PCT) (Culnan & Armstrong, 1999), which proposes that individuals make a rational cost-benefit analysis when making decisions about (technology) adoption. According to PCT, when users enjoy benefits like service personalization, but perceive a higher level of privacy risk, they are less likely to use the technology, even if the service itself offers considerable benefits (Li et al., 2015). However, in cases where users feel like the advantages of personalization outweigh the risks associated with privacy concerns, consumers are still willing to embrace the personalized content (Teepapal, 2024).

The Trust in AI Theory (Hoff & Bashir, 2015) posits that trust plays a crucial role in technology adoption. Users are more likely to accept AI-powered fitness applications if they believe that data privacy measures are in place and that the system operates transparently (Schuster & Habibipour, 2022). However, when trust is low, privacy concerns can become a significant barrier to adoption. For example, Son and Kim (2008) found that individuals are more likely to engage in privacy-protective behaviors (such as withholding information and rejecting services) when trust is low, which leads to lower technology adoption. In general, privacy and security of consumers' data is perceived as a critical factor in the use and adoption of mobile technologies in various fields of healthcare (Farzandipour et al., 2009).

Privacy concerns, therefore, are proposed to play a moderating role in the relationship between AI-driven service personalization and the adoption of AI-powered fitness apps (X. Zhang et al., 2014). When privacy concerns are high, the positive effect of personalization on adoption intention is weakened. In other words, users are less likely to adopt AI-powered fitness applications that offer personalized services if they perceive high privacy risks. On the contrary, when users trust the system's privacy measures and feel secure in the handling of their data, they are more likely to embrace personalized services, as the perceived benefits of personalization outweigh the potential loss of privacy (Hoff & Bashir, 2015).

Grounded in the established PCT and the trust in AI Theory, the literature on AI adoption in mHealth technologies, this research poses that privacy concerns act as a key moderator, weakening the positive effect of AI-driven personalization on users' intention to adopt AI-powered fitness applications.

H2: Privacy concerns negatively moderate the relationship between AI-driven service personalization and the intention to adopt AI-powered fitness apps, such that the positive effect of personalization is weaker when privacy concerns are high.

Digital assistants using AI or related technologies rely heavily on customers' personal information (Ebbers et al., 2020). Just like any other type of data, sensitive (health) data might be susceptible to data breaches, identity theft, and hacking (Tussyadiah et al., 2018). Such risks may increase customers' privacy concerns, decrease their trust in AI, and reduce their acceptance of AI technologies, leading to negative consequences for AI adoption (Martin & Murphy, 2016).

The growing popularity of wearable health devices and fitness applications has enabled extensive personal health monitoring, raising significant privacy concerns due to the real-time collection of sensitive user data (Sivakumar et al., 2024). Several studies have shown that perceived privacy risks significantly decrease the willingness to provide personal information on the Internet, particularly in health-related and mobile app contexts (Dinev & Hart, 2006). Privacy and security risks, including unauthorized access and data misuse, have been identified as direct barriers to technology adoption (Cho et al., 2009). Lidynia et al. (2018) confirmed that users of fitness apps and wearables often fear losing control over their data and unauthorized sharing of their personal information, which has a significant negative effect on the adoption of these technologies. Dhagarra et al. (2020) found that privacy concerns negatively and significantly affected intention to adopt mHealth services.

Privacy concerns negatively impact users' intentions to adopt AI-powered fitness and health technologies (Vimalkumar et al., 2021). Previous studies concluded that privacy concerns have a direct influence on adoption intention in mobile-based systems (Dinev & Hart, 2006; Sutanto et al., 2013). The findings of these studies suggest that online consumers' intentions to use personalized services are negatively affected by privacy concerns. Specifically, previous research has found that privacy concerns directly and negatively affect the acceptance and use of fitness trackers, wearable devices, and e-Health technologies (Reith et al., 2020; Singh, 2022; Schomakers et al., 2019). Therefore, the following hypothesis is proposed:

H3: Privacy concerns have a negative effect on the intention to adopt AI-powered fitness apps.

2.4 Conceptual Model

A visual representation of the conceptual model is shown in Figure 1, illustrating the proposed relationships and the personalization–privacy paradox—where personalization enhances adoption intention, but this effect is moderated by privacy concerns.

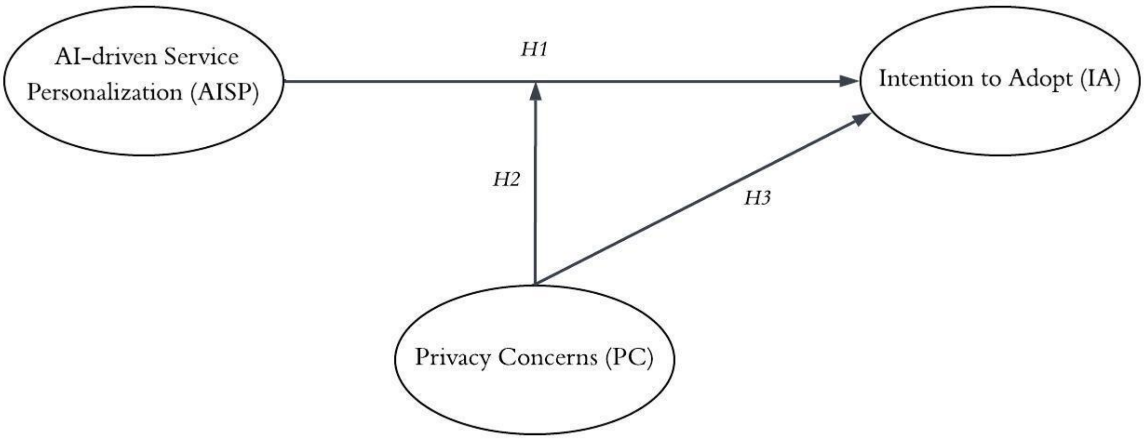

Figure 1: Conceptual Model

3. Methodology

3.1 Instrument Development

To gather the quantitative data used in this study, a reliable and contextually relevant survey instrument for AI-powered fitness applications is needed. The survey was based on existing literature and validated constructs and is divided into three sections. The first section introduced the concept of AI-powered fitness apps, together with an exemplary case that illustrated core features, such as real-time training, a virtual AI coach, dynamic adjustments, and progress tracking. The explanation also explained the types of user data they collect (e.g. heart rate, activity levels, body composition), and how this data is processed to generate personalized recommendations, using AI algorithms and Machine Learning. A video was included to help respondents visualize the concept. The full survey, including the use case description can be found in Appendix A.

The second section measured the core constructs in this research: Privacy Concerns (PC), AI-driven Service Personalization (AISP), and Intention to Adopt (IA). Items were adapted from previous verified literature and modified slightly to fit the context of AI-powered fitness apps (see Table 1). Privacy concerns (PC) was measured using five items, adopted from Dhagarra et al. (2020). AI-driven Service Personalization (AISP) was also measured using five items, adopted from Liu and Tao (2021). Intention to Adopt (IA) was measured using four items, adopted from Damberg (2021). All items were measured on a seven-point Likert scale ranging from 1 ("strongly disagree") to 7 ("strongly agree"). The operationalization of all constructs is summarized in Table 1.

The third and final section included demographic questions, including age, gender, education level, sports and fitness experience, and familiarity using fitness-based wearables or apps. These variables were included as control variables, based on previous research linking these to differences in technology adoption behavior. Research suggests that younger individuals are generally more open to adopting AI-driven technologies due to higher digital literacy and have more positive attitude toward innovation (Venkatesh et al., 2003). Also, men tend to view AI more positively than women (Armutat et al., 2024). Education level may have an influence on AI adoption, as individuals with higher education levels are more likely to embrace AI technologies (Dang et al., 2025). Also, individuals with greater exercise identity and fitness experience are more likely to adopt fitness apps (Barkley et al., 2020). Lee and Lee (2018) conclude that intention to adopt wearable fitness trackers is higher for consumers who are already familiar with the product, thus familiarity is suggested to have a positive influence on adoption behavior of AI-powered fitness apps.

Prior to launching the full survey, a pre-test was conducted with 5 participants to evaluate its clarity, utility, and relevancy. Based on feedback, minor adjustments were made to improve wording.

To reduce the potential for Common method bias (CMB), which might arise when the data of dependent and independent variables are collected from the same respondents (Chen et al., 2022), the survey assured anonymity and confidentiality, and neutral and non-leading phrasing in item wording (Larson, 2018). The Harman's single-factor test was conducted to statistically assess the presence of common method bias; results indicated that no single factor accounted for the majority (>50%) of variance, suggesting that CMB is unlikely to have significantly influenced the findings (Podsakoff et al., 2003).

Table 1. Constructs and Measurement Items

Construct	Definition	Original Item	Adapted Item	Source
Privacy Concerns (PC)	"Concerns for loss of privacy and need for protection against uncalled-for communication and misuse of personal information (Dhagarra et al., 2020)."	It bothers me when health providers ask me this much personal information.	It bothers me when AI-powered fitness apps ask me this much personal information.	(Dhagarra et al., 2020)
		I am concerned that health centres will be collecting too much of personal information.	I am concerned that AI-powered fitness apps will be collecting too much of personal information.	(Dhagarra et al., 2020)
		I am concerned that unauthorized people may access my personal information.	I am concerned that unauthorized people may access my personal information.	(Dhagarra et al., 2020)
		I am concerned that health providers may keep my personal information in non-accurate manner.	I am concerned that AI-powered fitness apps may keep my personal information in non-accurate manner.	(Dhagarra et al., 2020)
		I am concerned about giving information to health providers.	I am concerned about giving information to AI-powered fitness apps.	(Dhagarra et al., 2020)
AI-driven Service Personalization (AISP)	**Original:** "The degree to which smart healthcare services can provide specific health services based on consumers' own health information and conditions." (Liu & Tao, 2021) **Adapted**: "The degree to which AI-powered fitness apps can provide specific workout recommendations based users' personal fitness data and behavior."	Smart healthcare services provide personalized services that are based on my information.	AI-powered fitness apps provide personalized services that are based on my information.	(Liu & Tao, 2021)
		Smart healthcare services personalize my health management experience.	AI-powered fitness apps personalize my fitness training experience.	(Liu & Tao, 2021)
		Smart healthcare services personalize my health management by acquiring my personal preferences.	AI-powered fitness apps personalize my fitness experience by acquiring my personal preferences.	(Liu & Tao, 2021)
		Smart healthcare services personalize and deliver healthcare services to me according to my information.	AI-powered fitness apps personalize and deliver training programs to me based on my personal information.	(Liu & Tao, 2021)
		Smart healthcare services deliver personalized healthcare services.	AI-powered fitness apps deliver personalized fitness services.	(Liu & Tao, 2021)
Intention to Adopt (IA)	"The extent to which a consumer is likely to use a new technology." (Damberg, 2021)	I will always try to use fitness apps in my daily life.	I will always try to use AI-powered fitness apps in my daily life.	(Damberg, 2021)
		I plan to continue to use fitness apps frequently.	I plan to continue to use AI-powered fitness apps frequently.	(Damberg, 2021)
		I am determined to use my fitness app to monitor my exercise intensity in my daily life.	I am determined to use my AI-powered fitness app to monitor my exercise intensity in my daily life.	(Damberg, 2021)
		I intend to use my fitness app to monitor my exercise intensity in the future.	I intend to use my AI-powered fitness app to monitor my exercise intensity in the future.	(Damberg, 2021)

3.2 Sample

Similar to previous technology adoption studies (Lee & Chen, 2022), a convenience sampling method was adopted to identify respondents. The survey link was shared across different social media platforms and university group chats, together with a physical QR code in a fitness facility in Nijmegen to reach potential users in a relevant setting. The survey took care of ethical integrity, by integrating informed consent and ensuring privacy and confidentiality. All responses are anonymous, with no personally identifiable information being collected. Participants had the right to withdraw at any time without consequences. After eliminating 17 cases due to incomplete data, unrealistically short completion times, or response patterns indicating disengagement (e.g., selecting the same option across all items), 103 valid responses were received, giving a valid response rate of 86%. A summary of the sample demographics is presented in Table 2.

As depicted in Table 2, 53.4% of the respondents are males, and 44.7% are females. In terms of age, the majority of participants were relatively young, with nearly half (44.7%) aged 18–24 and 20.4% aged 25–34, while older age groups were less represented. The sample was relatively well-educated, with most respondents having completed a Bachelor's degree (29.1%), Master's degree (15.5%), or HBO (26.2%). One respondent (1.0%) had obtained a PhD. Others completed MBO (16.5%), or secondary education (11.7%). In response to the question "How would you rate your overall experience with fitness and sports (e.g., working out, training, participating in sports)?", most participants reported having either extensive (31.1%) or moderate (21.4%) experience. Smaller proportions indicated considerable (16.5%), some (18.4%), or very little experience (10.7%), while only 1.9% rated themselves as having expert-level experience. Regarding the question about the familiarity with using fitness-related apps (e.g., workout planners, tracking wearables), responses were relatively evenly distributed, with around 37.9% indicating low familiarity (not familiar at all or slightly familiar), while others reported moderate familiarity (18.4%), 19.4% being very familiar, 9.7% extremely familiar, and 1.0% expert-level familiar. Histograms with normal distribution curves are provided in Appendix B.

Table 2. Demographic attributes of the respondents

Variable	Options	Frequency (n)	Percentage (%)
Age	Under 18	1	1,0%
	18 - 24	46	44,7%
	25 - 34	21	20,4%
	35 - 44	6	5,8%
	45 - 54	8	7,8%
	55 - 64	16	15,5%
	65 - 74	5	4,9%
Gender	Male	55	53,4%
	Female	46	44,7%
	Non-binary / third gender	1	1,0%
	Prefer not to say	1	1,0%
Education	Secondary education	12	11,7%
	MBO	17	16,5%
	HBO	27	26,2%
	Bachelor's degree	30	29,1%
	Master's degree	16	15,5%
	Doctorate / PHD	1	1,0%
Experience with sports and fitness	Very little experience	11	10,7%
	Some experience	19	18,4%
	Moderate experience	22	21,4%
	Considerable experience	17	16,5%
	Extensive experience	32	31,1%
	Expert-level experience	2	1,9%
Familiarity with fitness apps and wearables	Not familiar at all	17	16,5%
	Slightly familiar	22	21,4%
	Somewhat familiar	14	13,6%
	Moderately familiar	19	18,4%
	Very familiar	20	19,4%
	Extremely familiar	10	9,7%
	Expert-level familiar	1	1,0%

3.3 Quantitative Data Analysis Strategy

The quantitative data collected in this study were analysed using IBM SPSS Statistics version 29 (SPSS v.29) (IBM Corp. Released, 2022). Before testing the hypotheses, several steps of regression diagnostics were conducted to evaluate the model assumptions and influential cases.

First, descriptive statistics, including means and standard deviations, were calculated for each item to provide an overview of central tendency and dispersion. Second, reliability testing was conducted using Cronbach's alpha (α) for each construct to assess internal consistency. A threshold of $\alpha \geq .70$ was used as the criterion for acceptable reliability (Hair et al., 2018).

To assess construct validity, an exploratory factor analysis (EFA) was performed using Principal Axis Factoring with Varimax rotation, which assumes uncorrelated factors (Grieder & Steiner, 2021), in line with the theoretical expectation of independence between constructs. Unlike Principal Component Analysis (PCA), which includes total variance, PAF focuses exclusively on shared (common) variance, which makes it more suitable for identifying latent constructs (Costello & Osborne, 2005). Additionally, PAF is preferred when data show some deviation from normality (Fabrigar et al., 1999), which was the case for some items in this dataset. Each construct was analysed separately to confirm that items loaded clearly and only onto a single factor. Items were expected to load at $\geq .70$ on their intended construct without substantial cross-loadings.

The factor structure was further evaluated by inspecting the scree plot and applying the eigenvalue > 1 criterion (Kaiser, 1960), which supported the expected three-factor solution corresponding to the underlying theoretical constructs. The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and Bartlett's test of sphericity were examined to ensure that the data were suitable for factor analysis (Cerny & Kaiser, 1977).

Before proceeding to the regression analysis, key assumptions were checked, including normality of residuals, linearity, homoscedasticity, multicollinearity, and outlier analyses. Normality was assessed using skewness and kurtosis values. Linearity and homoscedasticity were assessed through P–P plots and scatterplots. The variance inflation factor (VIF) was used to evaluate multicollinearity among variables. Hair et al. (2018) recommend a threshold of 3 to avoid interpretation or estimation problems. Also, to reduce multicollinearity and improve interpretability, the independent variables (AISP and PC) were mean-centered prior to computing the interaction term. These centered variables were used in the hierarchical regression analysis testing for moderation (Aiken et al., 1991). Outliers were examined via standardized residuals and boxplots. Bootstrapping tests with 5000 resamples and a 95% bias-corrected confidence interval were used to test the robustness of the regression coefficients, as proposed by Hayes (2013). However, this paper reports the results from the regular regression models without the bootstrapping tests since both results were similar.

3.4 Additional Analytical Considerations

In addition to the primary constructs, the survey also included two exploratory variables: Perceived Usefulness (PU) and Willingness to Disclose Information for Personalization (DIP). PU was included as an extra construct because it is proven to be one of the most influential factors in shaping users' attitudes and behavioral intentions towards adopting new technologies, particularly in AI contexts (Ibrahim et al., 2025; Kelly et al., 2022). The Technology Acceptance Model (TAM), originally developed by Davis (1989), identifies Perceived Usefulness (PU) as a core belief influencing whether individuals are willing to adopt a system. PU is defined as "the extent to which a person believes that using a particular system will improve his/her performance" (Davis, 1989), and has been consistently validated as a key determinant in user acceptance of both traditional and AI-driven systems (Wang et al., 2023).

DIP measured users' openness to sharing personal data in exchange for personalized services. It can be understood through the Privacy calculus (as explained in chapter 2.3), where users are willing to disclose personal data in return for perceived benefits, such as personalized content (Cloarec et al., 2024). Strong privacy concerns could then reduce the willingness to disclose personal information, and use personalized services. In contrast it is proven that, in platforms that generate short-term positive affect (e.g. personalized content, good user experience), users are more inclined to share personal information (Cloarec et al., 2024).

To test for possible moderation and mediation effects of these two variables, this study employed Hayes' PROCESS macro for SPSS (version 5.0). Specifically, Model 1 was used to explore whether PU and DIP (independently) moderated the relationship between AISP and IA. Model 4 was used to test whether either variable mediated the relationship between AISP and IA. The results revealed that neither variable acted as a significant moderator or mediator in the hypothesized relationships.

Furthermore, including PU and DIP into the full model disrupted the relationships between the core constructs (AISP, PC, and IA), leading to multicollinearity issues. Therefore, both were ultimately excluded from the final model to preserve theoretical clarity and model simplicity, as the primary focus of this study was the privacy-personalization paradox.

Although the gender variable included categories for non-binary individuals and those who preferred not to disclose their gender, both categories contained only one respondent. Including these groups as dummy variables led to unstable regression estimates due to the lack of variability. Therefore, these two categories were excluded from the regression analyses, and gender was included as a binary variable (0 = male [reference group], 1 = female).

4. Results

4.1 Reliability and convergent validity

To evaluate the measurement quality of the constructs, several criteria were examined to ensure reliability and convergent validity, following established recommendations in the literature.

First, descriptive statistics are given for each item, including the Mean and Standard Deviation, as depicted in table 3. Additional descriptive statistics and distribution plots for each construct can be found in Appendix C. Means ranged from 3.48 to 5.42, indicating moderate to high levels of agreement among participants across items. All factor loadings exceeded the recommended threshold of 0.70 (Hair et al., 2018), indicating acceptable indicator reliability. No items had to be deleted. Internal consistency was assessed using Cronbach's Alpha, which ranged from 0.92 to 0.96 across the constructs, exceeding the commonly accepted threshold of 0.70 (Hair et al., 2018). Furthermore, composite reliability (CR) values for all constructs were above 0.70 (Urbach & Ahlemann, 2010), and average variance extracted (AVE) values were greater than 0.50 (see Table 3). Together, the results support both the reliability and convergent validity of the measurement instrument (Fornell & Larcker, 1981).

Exploratory factor analysis (EFA) was performed to confirm the dimensionality of the construct within the sample. The analysis revealed three distinct factors with Eigenvalues greater than 1.0, which together explained 78.0% of the total variance (see Appendix E, Figure 9). The first latent variable explained 28,3% of the total variance, thus common method bias is not an issue. Each factor corresponded to one of the predefined constructs, supporting the structural validity of the measurement model in this context. Also, the data's suitability for factor analysis was confirmed: the Kaiser-Meyer-Olkin (KMO) value was 0.872, which falls within the "meritorious" category according to Kaiser (1974), and Bartlett's test of sphericity was statistically significant ($p < 0.05$), indicating strong suitability for factor analysis (Cerny & Kaiser, 1977).

Table 3. Measurement Model Summary: Descriptive Statistics, Factor Loadings, and Reliability Indicators

	α	CR	AVE	Factor Loadings	Mean	Std. Deviation
Privacy Concerns (Variance explained = 28,3%)	0,917	0,92	0,70			
PC1				0,909	4,52	1,644
PC2				0,93	4,77	1,676
PC3				0,774	5,25	1,539
PC4				0,74	4,65	1,637
PC5				0,801	4,48	1,787
AI-driven Service Personalization (Variance explained = 25,2%)	0,948	0,95	0,79			
AISP1				0,884	5,32	1,285
AISP2				0,926	5,34	1,325
AISP3				0,817	5,28	1,353
AISP4				0,918	5,42	1,303
AISP5				0,891	5,31	1,372
Intention to Adopt (Variance explained = 24,5%)	0,958	0,96	0,85			
IA1				0,873	3,48	1,873
IA2				0,959	3,64	1,852
IA3				0,929	3,5	1,814
IA4				0,928	3,89	1,894

4.2 Discriminant Validity

Discriminant validity was examined through the factor loading pattern produced in the exploratory factor analysis. Each item loaded strongly on its respective construct (all primary loadings > 0.70) and showed no substantial cross-loadings on other factors (all secondary loadings < 0.30), indicating that the constructs are empirically distinct (see table 4). This supports the discriminant validity of the measurement model, in line with recommended EFA practices (Costello & Osborne, 2005).

The AVE values for the individual constructs were compared with the shared variance between all possible pairs of constructs. The results revealed that for each construct, the AVE was much higher than its maximum shared variance (MSV) with other constructs, thus supporting discriminant validity (Hair et al., 2018).

Pearson correlation coefficients were examined to assess the direction and strength of the relationships between the core constructs (see Appendix D). The correlations revealed that Privacy Concerns (PC) were significantly and negatively correlated with both AI-driven Service Personalization (AISP) ($r = -.311$, $p = .001$) and Intention to Adopt (IA) ($r = -.314$, $p = .001$). AISP was positively and significantly associated with IA ($r = .419$, $p < .001$). These results are consistent with the hypothesized relationships and provide preliminary support for the privacy–personalization paradox in the context of AI-powered fitness applications.

Table 4. Rotated Factor Matrix

	PC	**AISP**	**IA**
PC1	0,886		
PC2	0,922		
PC3	0,769		
PC4	0,724		
PC5	0,761		
AISP1		0,873	
AISP2		0,895	
AISP3		0,775	
AISP4		0,895	
AISP5		0,851	
IA1			0,847
IA2			0,919
IA3			0,913
IA4			0,874

Extraction Method: Principal Axis Factoring.
Rotation Method: Varimax with Kaiser Normalization.
Factor loadings < 0,3 not displayed

4.3 Regression Assumptions

Key assumptions for regression analysis were tested to ensure validity of the results. Normality of residuals was assessed through P–P plots, indicating that residuals were approximately normally distributed (Appendix E, Figure 6). Homoscedasticity was evaluated using scatterplots of standardized residuals against predicted values, showing no major violations (Appendix E, figure 7). Linearity was evaluated by inspecting residual plots (Appendix E, Figure 8).

The variance inflation factor (VIF) was used to evaluate multicollinearity among variables. According to Hair et al. (2018), VIF values higher than 3 may result in interpretation or estimation problems. In this study, PC and AISP showed a VIF values of respectively 1,165 and 1,257 (Appendix F), indicating no concerns regarding multicollinearity. Outlier detection was performed using boxplots (Appendix B) and standardized residuals, with no cases exceeding |3.0|, suggesting no influential outliers.

Additionally, the distribution of individual items was inspected for univariate normality. Univariate skewness of each item ranged in the acceptable interval of |2|. Considering the kurtosis of the items, most variables fell within acceptable thresholds, but the AISP items showed elevated kurtosis (>2), indicating a slightly leptokurtic distribution. As the AISP construct is measured using ordinal Likert-type items, such deviations are not uncommon (Finney, 2013).

4.4 Hierarchical Regression analysis

To test the hypothesized relationships, a hierarchical regression analysis was conducted. This approach allows for the stepwise inclusion of control variables, main predictors, and interaction terms, enabling the evaluation of each block's incremental explanatory power. In the first step, the control variables (age, gender, education, experience, and familiarity) were entered. In the second step, the main predictors AISP and PC were added. In the third and final step, the interaction term AISP × PC was included to test for moderation. This stepwise approach allows for the examination of the incremental explanatory power of each block (Hair et al., 2018). The findings are summarized in table 5.

Model 0: Control variables

The base model including age, gender, education level, prior experience with sports and fitness, and familiarity with fitness apps and wearables explained 7% of the variance in adoption intention ($R^2 = 0.07$, Adjusted $R^2 = 0.022$), though this model was not statistically significant, $F(5, 97) = 1.469$, $p = .207$. Among the control variables, only *familiarity with fitness apps and wearables* was a significant predictor ($\beta = 0.31$, $t = 2.473$, $p < .05$), indicating that prior exposure to digital fitness technologies was positively associated with adoption intention.

Model 1: Main Predictors

Introducing the two key independent variables (PC and AISP) led to a significant improvement in the model fit ($\Delta F = 11.824$, $p < .01$), explaining 25.6% of the variance in adoption intention ($R^2 = 0.256$, Adjusted $R^2 = 0.201$). AI-driven Service Personalization proved to be a strong positive predictor ($\beta = 0.34$, $t = 3.426$, $p < .01$), suggesting that higher perceived personalization through AI significantly increased users' adoption intentions. In contrast and as expected, Privacy Concerns had a negative and significant effect ($\beta = -0.222$, $t = -2.321$, $p < .05$), indicating that heightened concerns about data privacy reduced the likelihood of consumers adopting such applications. The effect of familiarity with fitness apps remained significant ($\beta = 0.242$, $t = 2.094$, $p < .05$).

Model 2: Interaction Effect

In the final model, the interaction term between Privacy Concerns and AI-driven Service Personalization was added to test for a potential moderating effect. However, the interaction term was non-significant ($\beta = 0.019$, $t = 0.184$, $p > .05$), and did not contribute to an increase in explained variance ($\Delta F = 0.034$, $p > .05$). Thus, there was no evidence to support a moderation effect of privacy concerns on the relationship between personalization and adoption intention. These results will be discussed further in chapter 5. It is important to note that when an interaction term is included in a regression model, the independent variables no longer reflect their overall impact (Aiken & West, 1991), which makes them harder to interpret. Nevertheless, in this case, the main effects of AI-driven Service Personalization ($\beta = 0.332$, $t = 3.052$, $p < .01$) and Privacy Concerns ($\beta = -0.221$, $t = -2.306$, $p < .05$) remained statistically significant and in the expected directions.

Since including the interaction term did not significantly improve the model ($\Delta F = 0.034$, $p > .05$) and led to a slight decrease in adjusted R^2 (from .201 to .193), Model 1 is used as the final model. This choice aligns with the suggestions of K. P. Burnham and Anderson (2003), preferring a simpler model when additional predictors do not meaningfully enhance explanatory power (Burnham & Anderson, 2002).

Table 5. Hierarchical Regression Results

Predictors	**Model 0**			**Model 1**			**Model 2**		
	B	**std. Error**	**β (t)**	**B**	**std. Error**	**β (t)**	**B**	**std. Error**	**β (t)**
Control variables									
Age	-0,05	0,108	-0,049 (t =-0,467)	0,017	0,1	0,016 (t=0,167)	0,016	0,101	0,016 (t=0,161)
Gender (Male = 0; 53,4%; Female = 1; 44,7%)	-0,208	0,351	-0,059 (t=-0,591)	0,232	0,33	0,066 (t=0,702)	0,233	0,332	0,066 (t=0,7)
Education	-0,057	0,163	-0,041 (t=-0,348)	0,069	0,15	0,05 (t=0,462)	0,072	0,152	0,052 (t=0,477)
Experience with sports and fitness	-0,135	0,178	-0,109 (t=-0,755)	-0,159	0,165	-0,129 (t=-0,968)	-0,158	0,166	-0,128 (t=-0,956)
Familiarity with fitness apps and wearables	0,327	0,132	0,31* (t=2,473)	0,255	0,122	0,242* (t=2,094)	0,259	0,124	0,246* (t=2,088)
Independent Variables									
Privacy Concerns				-0,27	0,116	-0,222* (t=-2,321)	-0,27	0,117	-0,221* (t=-2,306)
AI-driven Service Personalization				0,492	0,144	0,34** (t=3,426)	0,481	0,158	0,332** (t=3,052)
Interaction Term									
PC * AISP							0,015	0,079	0,019 (t=0,184)
R-squared	0,07			0,256			0,256		
Adjusted R-squared	0,022			0,201			0,193		
F-Change	1,469			11,824**			0,034		

* = significant at the 0.05 level (p<0.05)
** = significant at the 0.01 level (p<0.01)

5. Discussion

The aim of this study was to investigate how privacy concerns and AI-driven service personalization influence users' intention to adopt AI-powered fitness applications, contributing to a deeper understanding of the privacy–personalization paradox. The findings offer clear support for the first and third hypotheses: AI-driven personalization significantly enhances users' adoption intentions, whilst privacy concerns have a negative influence.

The first hypothesis (H1) assumed that AI-driven service personalization positively affects users' intention to adopt AI-powered fitness applications. The regression analysis revealed that AISP indeed had a significant positive effect on adoption intention ($\beta = 0.34$, $p < 0.01$). This result is in line with previous academic research in the mobile health domain, where personalization has been found out to be a key determinant of adoption (Chin et al., 2022; Farrokhi et al., 2021). It supports the idea that users are more likely to accept a technology that is personalized to their needs and wants. These results highlight the importance of personalization in increasing the adoption of AI-powered fitness apps. It is also in line with the Task-Technology Fit (TTF) model (Goodhue & Thompson, 1995), as it shows that a better fit between the technology (due to AI-personalization) and the user's goals, leads to a more positive perception of the app.

Surprisingly, privacy concerns did not moderate the relationship between AI-driven service personalization and intention to adopt AI-powered fitness apps, which means that the second hypothesis (H2) cannot be confirmed. The regression results did not find a significant interaction effect ($\beta = 0.019$, $t = 0.184$), indicating that, in this model, privacy concerns did not moderate the relationship as hypothesized. This was somewhat unexpected, given the strong theoretical foundation, based on the Privacy Calculus Theory (PCT) (Culnan & Armstrong, 1999) and the Trust in AI theory (Hoff & Bashir, 2015). Several explanations can be given for this finding.

One possible explanation for this unexpected finding is the statistical characteristics of the data. First, the overall sample size ($N = 103$), which is sufficient for detecting main effects, may have limited the statistical power required to detect more subtle interaction effects. Interaction terms often require larger samples due to their typically small effect sizes and increased standard errors (VanderWeele & Knol, 2014). Second, the distribution of the AI-driven service personalization variable (AISP) had a moderately high kurtosis of 3,9, which may have limited the variability required to detect a moderation effect. Interaction terms typically rely on a sufficient spread across both the predictor and moderator variables (Aguinis et al., 2016).

Apart from these possible statistical issues, a more likely explanation may lie in the nature of the relationship between personalization and privacy concerns. In stead of acting as a moderator, privacy concerns might independently or additively influence adoption, apart from the degree of personalization. In this way, the two forces act parallel to each other, rather than interacting. This suggests a model that describes a more straightforward or less complex interpretation of the privacy–personalization paradox than is often theorized.

That said, an alternative interpretation is that the relationship between personalization, privacy concerns, and adoption is not more straightforward, but rather substantially more complex than the current model is able to capture. It is also possible that privacy concerns interact with other latent variables, such as trust in technology, perceived control over data, or motivation to achieve health goals (Alaiad et al., 2019; Dhagarra et al., 2020; Vimalkumar et al., 2021). In this view, the absence of an interaction effect between personalization and privacy concerns is caused because there exist more nuanced mechanisms, such as conditional moderation, mediated effects, or non-linear dynamics, including other factors. For example, privacy concerns may only reduce the effect of personalization when users have low trust in AI systems (Liu & Tao, 2021).

Finally, the absence of a moderation effect may be due to the context-specific nature of the privacy–personalization paradox. How users weigh the trade-off between personalization and privacy may differ across different contexts. This is in line with Sheng et al. (2008), who found that the effects of personalization and customers' privacy concerns on intention to adopt vary according to the situation or context. They concluded that the difference between customers' privacy concerns for personalized services versus non-personalized services is greater in a non-emergency than in an emergency context because emergencies can trigger customers' needs for personalization services and diminish their privacy concerns.

The third hypothesis (H3), which proposes that privacy concerns have a negative effect on the intention to adopt AI-powered fitness apps, can be confirmed. The regression analysis showed that privacy concerns significantly decreased the intention to adopt ($\beta = -0.22$, $p < 0.05$). This finding is in line with prior research, which suggests that privacy concerns are a significant barrier to the adoption of mHealth technologies (Farzandipour et al., 2009; Reith et al., 2020; Vimalkumar et al., 2021). So, even though AI-driven personalization improves the app's functionality, privacy risks related to data misuse and unauthorized access can at the same time decrease users' intention to adopt the technology (Teepapal, 2024).

In addition to the main constructs, two conceptually relevant variables, Perceived Usefulness (PU) and Disclosure Intention (DIP) were considered in the survey. When building a model where PU is the only predictor of adoption intention (Appendix F, figure 11), PU emerged as a highly significant predictor of adoption intention ($\beta = .607$, $p < .001$). This suggests that PU plays a central role in shaping users' willingness to adopt AI-powered fitness applications, in line with the assumptions of the Technology Acceptance Model (TAM). However, PU was excluded from the final model, as its strong correlation with AI-driven personalization introduced multicollinearity issues and reduced model simplicity. Also, further statistic tests found that PU did not significantly mediate or moderate the effects of either AI-driven service personalization or privacy concerns in this dataset.

Disclosure Intention (DIP) was also examined in a separate regression model (Appendix F, figure 12). The analysis revealed that DIP had a significant positive effect on intention to adopt ($\beta = .354$, $p < .001$), indicating that users who were more willing to disclose personal information were also more inclined to adopt AI-powered fitness apps. This finding aligns with previous research suggesting that users' willingness to share data is a key enabler in contexts where personalization depends on personal input (Chellappa & Sin, 2005). However, similar to PU, DIP was excluded from the final model for theoretical and methodological clarity, as it did not significantly mediate or moderate the effects of either personalization or privacy concerns.

6. Conclusion

This study explored how AI-driven personalization and privacy concerns influence the intention to adopt AI-powered fitness applications, addressing the phenomenon known as the privacy-personalization paradox. Using a quantitative approach, the findings confirmed that AI-driven service personalization significantly increases adoption intentions, highlighting the importance of tailoring fitness services to individual needs. Additionally, privacy concerns reduce users' willingness to adopt AI-powered fitness apps. In contrary to the expectations, privacy concerns did not moderate the relationship between personalization and adoption. This suggests that, in this specific study's context, privacy concerns and personalization do not interact, but rather operate as independent forces on adoption intention. Exploratory analysis revealed that Perceived Usefulness (PU) and Willingness to Disclose Information for Personalization (DIP) also have a strong influence on adoption intention. They were however not included in the final regression model due to multicollinearity issues and to preserve model simplicity. In conclusion, this research contributes to the growing body of literature on AI adoption by empirically testing the role of personalization and privacy in shaping user behavior toward AI-powered fitness applications. The absence of a moderation effect invites further exploration of more nuanced relationships in future studies.

6.1 Theoretical implications

This study offers several meaningful contributions to theory. Firstly, as the privacy-personalization paradox has been widely explored in contexts such as e-commerce, smart home devices, and social media (e.g., Aguirre et al., 2016; Cloarec et al., 2024), this research extends this phenomenon to the context of AI-powered fitness applications, where sensitive personal data (e.g. heart rate, sleep patterns, body composition) is required. Secondly, the conclusions of this research support the core assumptions of the Technology Acceptance Model (TAM) and the Task-Technology Fit (TTF) model. That is, while the perceived alignment between a technology and a user's personal needs (TTF), as well as its perceived usefulness (TAM), are important precursors to adoption. Also, privacy concerns over data security are proven to act as a barrier, which supports findings in previous literature and aligns with the Privacy Calculus Theory (PCT) and the Trust in AI framework.

6.2 Practical implications

This study also provides practical insights for app developers and fitness tech companies. First, the clear impact of AI-driven service personalization on adoption underscores the importance of tailoring fitness recommendations to individual needs and preferences. Fitness app developers should invest in AI algorithms that continuously adapt and improve recommendations based on user data. Also, these findings are relevant for personal trainers who integrate digital tools into their services. They could utilize AI algorithms to personalize programs more efficiently, thereby leaving more time to focus on relationship-building and coaching quality. Secondly, the negative effect of privacy concerns on adoption highlights the need for transparent data practices, while using AI algorithms. Practices such as incorporating clear privacy policies, visible data security measures and encrypting personal data can help build trust and decrease privacy concerns (Rouhelo, 2024). Lastly, it should be noted that personalization and privacy do not have to be treated as a trade-off, but rather as parallel design constructs. Prioritizing one should not come at the cost of the other. App designers can create user experiences that are both personalized and take care of mitigating privacy concerns.

6.3 Limitations and directions for future research

While this study offers valuable insights into the adoption of AI-powered fitness applications, several limitations can be acknowledged.

First, the sample size (N = 103) was adequate for detecting main effects, but may have been too small to detect the proposed interaction effect. Future studies should aim for larger and more diverse samples to improve statistical power and generalizability.

Second, because self-reported measures and a convenience sampling strategy, this introduces potential biases, such as social desirability or an overrepresentation digitally literate, younger, and more fitness-oriented individuals. Employing more controlled sampling techniques could increase the generalizability of future findings.

Third, because of the scope of the study, it focused on a relatively narrow set of variables: AI-driven service personalization, privacy concerns, and adoption intention. This allowed for a focused analysis, but it also likely oversimplifies the full range of psychological and contextual factors influencing adoption, thereby also oversimplifying the privacy-personalization paradox. Future research could expand the model by including constructs such as trust in AI, perceived data control, health motivation, or technology anxiety, which may also affect the adoption of AI-powered fitness apps.

Fourth, while the scale of the privacy concerns construct were validated and had good reliability and validity, the conceptualization may not fully capture its complexity. Research found that there are different types of privacy concerns, including information, physical and social privacy concerns (Zhang et al, 2022). Conceptualizing such distinctions could lead to a better understanding which specific concerns most strongly influence adoption behavior.

Finally, while personalization proved to be an important predictor of adoption, this study did not measure whether users really experienced personalized content, only whether they perceived it based on a hypothetical scenario. Future research could explore actual usage in real-world settings, using experiments to investigate behavior over time. Applying such research techniques would provide deeper insights into how perceptions of AI-powered fitness lead to actual usage, going beyond investigating the perceived personalization and intention to adopt.

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Appendix A: Survey AI-Powered Fitness Application

Survey AI-powered Fitness Apps

Start of Block: Welcome Page

Understanding the Adoption of AI-powered Fitness Apps

Dear Participant, Thank you for participating in this study! In this survey, we will investigate your behavioral intentions regarding the use of AI-powered fitness applications.
AI-powered fitness apps are designed to provide a fully personalized and dynamic training experience, using AI algorithms. Before signing up, the app asks for personal data such as your age, weight, gender, fitness level, goals, and available workout equipment. During your training, the app collects biometrical data like heartrate, and burned calories by syncing to your smartwatch or other smart devices.
Based on this data, the AI algorithm learns over time in order to generate a scientifically grounded training plan tailored specifically to your objectives and data. The AI-algorithm continuously adapts its recommendations, based on your personal interaction with the app.

*In contrast***:** *Non-AI fitness apps offer fixed workout programs or a range of exercises you can click on. They provide the same routines to all users. They use no personal, or only basic data.*

By clicking on the “I agree to participate in this study” button below, you indicate that:
You have read and understood the information provided above.
You voluntarily agree to participate in this study.
You understand that your responses will be stored securely and anonymously, and used for research purposes only.
You are aware that you can withdraw from the study at any time.

- o I agree to participate in this study (1)
- o I do not agree to participate in this study (2)

End of Block: Welcome Page

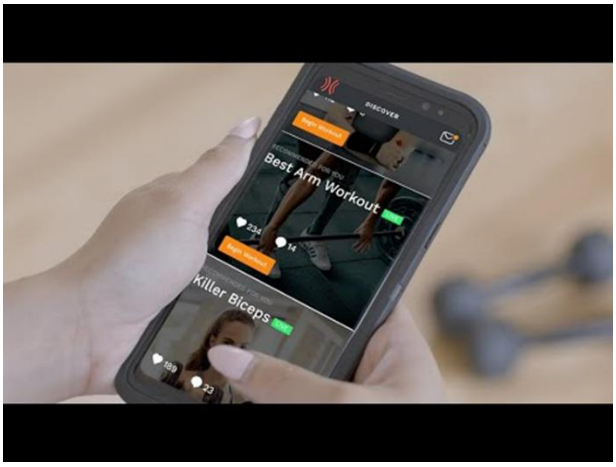
Start of Block: Survey Introduction

Introduction Fitfi

Imagine you are using Fitfi.

- After entering your age, weight, and fitness goals, the app customizes its features to suit your needs.
- During your workout, the app uses your smartphone's camera to monitor your form and syncs with your smartwatch to track heart rate and calories.
- The AI algorithm adjusts your workout in real-time based on your behavior, preferences and biometrical data.
- The app provides personalized recommendations for exercises, nutrition, and recovery.
- After each session, your workouts are updated based on your progress and performance.

To get a better understanding of how Fitfi works, I invite you to watch a 1-minute video for a visual representation of the app:



5Gear Studios. (2024, 14 juni) Fitfi AI Fitness App Web Commercial [Video]. YouTube. Retrieved May 19 2025, from https://www.youtube.com/watch?v=bdbPO39z8-w

End of Block: Survey Introduction

Start of Block: Main Questions

Q1 Privacy Concerns

The next section focuses on Privacy Concerns, which refers to how worried you are about the security and misuse of your personal data when using AI-powered fitness apps.

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
It bothers me when AI-powered fitness apps ask me this much personal information. (1)	○	○	○	○	○	○	○
I am concerned that AI-powered fitness apps will be collecting too much of personal information. (2)	○	○	○	○	○	○	○
I am concerned that unauthorized people may access my personal information. (3)	○	○	○	○	○	○	○
I am concerned that AI-powered fitness apps may keep my personal information in non-accurate manner. (4)	○	○	○	○	○	○	○
I am concerned about giving information to AI-powered fitness apps. (5)	○	○	○	○	○	○	○

Page Break

Q2 Perceived (AI-driven) Personalization The next section focuses on Perceived (AI-driven) Personalization, which refers to how much you believe that AI-powered fitness apps understand and represent your personal needs and preferences.

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
AI-powered fitness apps provide personalized services that are based on my information. (1)	o	o	o	o	o	o	o
AI-powered fitness apps personalize my fitness training experience. (2)	o	o	o	o	o	o	o
AI-powered fitness apps personalize my fitness experience by acquiring my personal preferences. (3)	o	o	o	o	o	o	o
AI-powered fitness apps personalize and deliver training programs to me based on my personal information. (4)	o	o	o	o	o	o	o
AI-powered fitness apps deliver personalized fitness services. (5)	o	o	o	o	o	o	o

Page Break

Q3 Perceived Usefulness
The next section focuses on Perceived Usefulness, which refers to how much you believe using AI-powered fitness apps will help you improve your performance or achieve your fitness goals.

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
Using AI-Powered fitness apps during exercise would enable me to accomplish tasks more easily. (1)	○	○	○	○	○	○	○
Using AI-Powered fitness apps would improve my exercise performance. (2)	○	○	○	○	○	○	○
Using AI-Powered fitness apps during exercise would increase my productivity. (3)	○	○	○	○	○	○	○
Using AI-Powered fitness apps would enhance my effectiveness when exercising. (4)	○	○	○	○	○	○	○
Using AI-Powered fitness apps would make it easier to do exercise. (5)	○	○	○	○	○	○	○
I would find AI-Powered fitness apps useful in fitness. (6)	○	○	○	○	○	○	○

Page Break

Q4 Disclosing information for Personalization
The next section focuses on Perceived (AI-driven) Personalization, which refers to how much you believe that AI-powered fitness apps understand and represent your personal needs and preferences by disclosing your information.

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
By disclosing my information, the AI-powered fitness app can understand what I need in my workout. (8)	o	o	o	o	o	o	o
By disclosing my information, the AI-powered fitness app can know what I want. (9)	o	o	o	o	o	o	o
By disclosing my information, the AI-powered fitness app will take my needs as its own preferences. (10)	o	o	o	o	o	o	o

Page Break

Q5 Intention to adopt AI-powered Fitness apps
The next section focuses on Intention to Adopt, which refers to how likely you are to use AI-powered fitness apps in the future to support your fitness goals.

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
I will always try to use AI-powered fitness apps in my daily life. (1)	o	o	o	o	o	o	o
I plan to continue to use AI-powered fitness apps frequently. (2)	o	o	o	o	o	o	o
I am determined to use my AI-powered fitness app to monitor my exercise intensity in my daily life. (3)	o	o	o	o	o	o	o
I intend to use my AI-powered fitness app to monitor my exercise intensity in the future. (4)	o	o	o	o	o	o	o

End of Block: Main Questions

Start of Block: Demographic Questions

Demographics: Age, gender, education, experience, and familiarity

Q6 What is your age?

- Under 18 (1)
- 18 - 24 (2)
- 25 - 34 (3)
- 35 - 44 (4)
- 45 - 54 (5)
- 55 - 64 (6)
- 65 - 74 (7)
- 75 - 84 (8)
- 85 or older (9)

Q7 What is your gender?

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

Q8 What is the highest level of education you have completed?

- Primary education (1)
- Secondary education (2)
- MBO (3)
- HBO (4)
- Bachelor's degree (5)
- Master's degree (6)
- Doctorate / PHD (7)

Q9 How would you rate your overall experience with fitness and sports (e.g., working out, training, participating in sports)?

- o No experience (1)
- o Very little experience (2)
- o Some experience (3)
- o Moderate experience (4)
- o Considerable experience (5)
- o Extensive experience (6)
- o Expert-level experience (7)

Q10 How familiar are you with using fitness-related apps (e.g., workout planners, tracking wearables)?

- o Not familiar at all (1)
- o Slightly familiar (2)
- o Somewhat familiar (3)
- o Moderately familiar (4)
- o Very familiar (5)
- o Extremely familiar (6)
- o Expert-level familiar (7)

End of Block: Demographic Questions

End of survey message

Thank you for participating!
Your responses have been recorded successfully.
If you have any questions or concerns about this research, please contact:

Luc van Rooij
Radboud University Nijmegen
Luc.vanrooij@ru.nl

Appendix B: Sample Characteristics

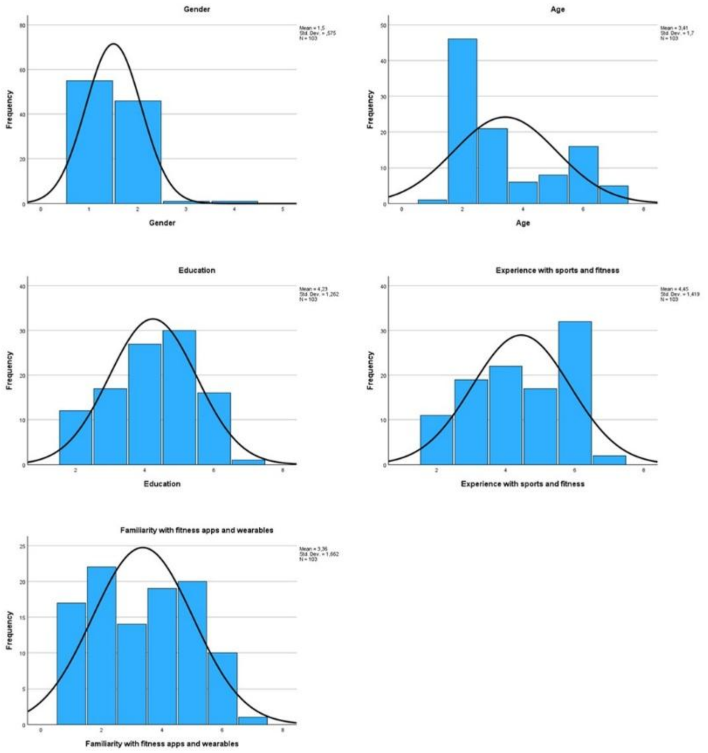


Figure 2: Histograms with Normal Curves for Demographic Variables

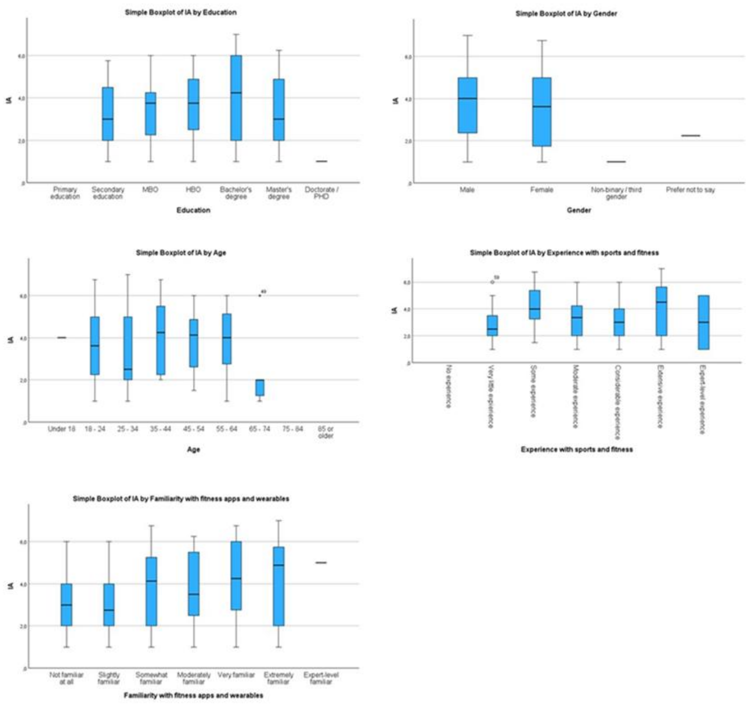
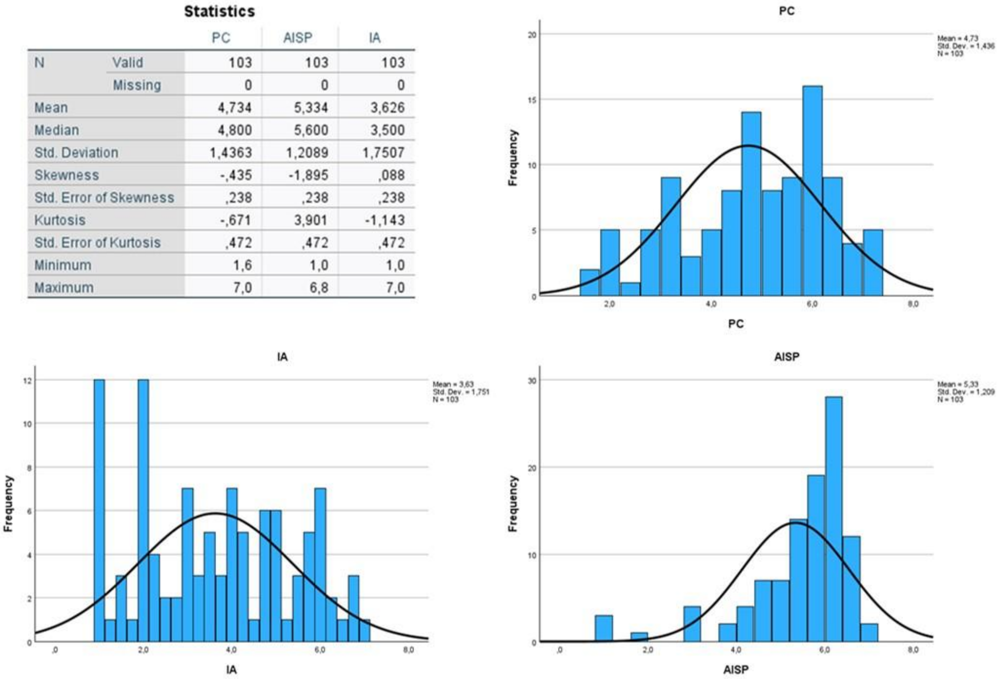


Figure 3: Boxplots of Intention to Adopt (IA) by Demographic Variables

Appendix C: Constructs and measurement



Statistics

		PC	AISP	IA
N	Valid	103	103	103
	Missing	0	0	0
Mean		4,734	5,334	3,626
Median		4,800	5,600	3,500
Std. Deviation		1,4363	1,2089	1,7507
Skewness		-,435	-1,895	,088
Std. Error of Skewness		,238	,238	,238
Kurtosis		-,671	3,901	-1,143
Std. Error of Kurtosis		,472	,472	,472
Minimum		1,6	1,0	1,0
Maximum		7,0	6,8	7,0

Figure 4: Descriptive Statistics and Distributions of Key Constructs

Appendix D: Correlation Matrix

Correlations

		PC	AISP	IA
PC	Pearson Correlation	--		
	N	103		
AISP	Pearson Correlation	-,311**	--	
	Sig. (2-tailed)	,001		
	N	103	103	
IA	Pearson Correlation	-,314**	,419**	--
	Sig. (2-tailed)	,001	<,001	
	N	103	103	103

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

Figure 5: Pearson Correlation Matrix for Key Constructs

Appendix E: Reliability and Validity Checks

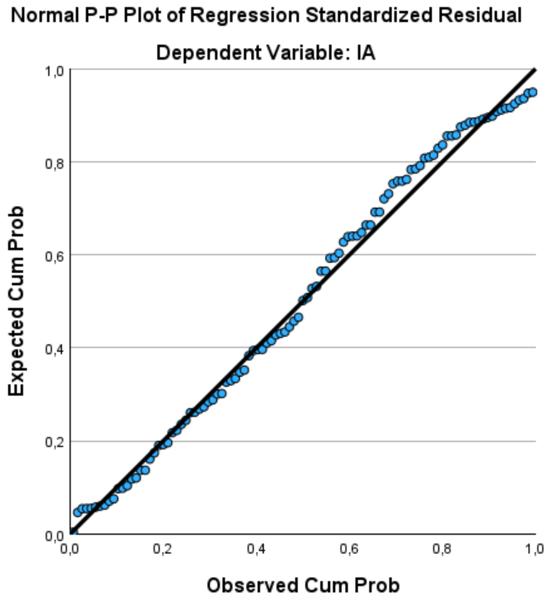


Figure 6: Normality of Residuals

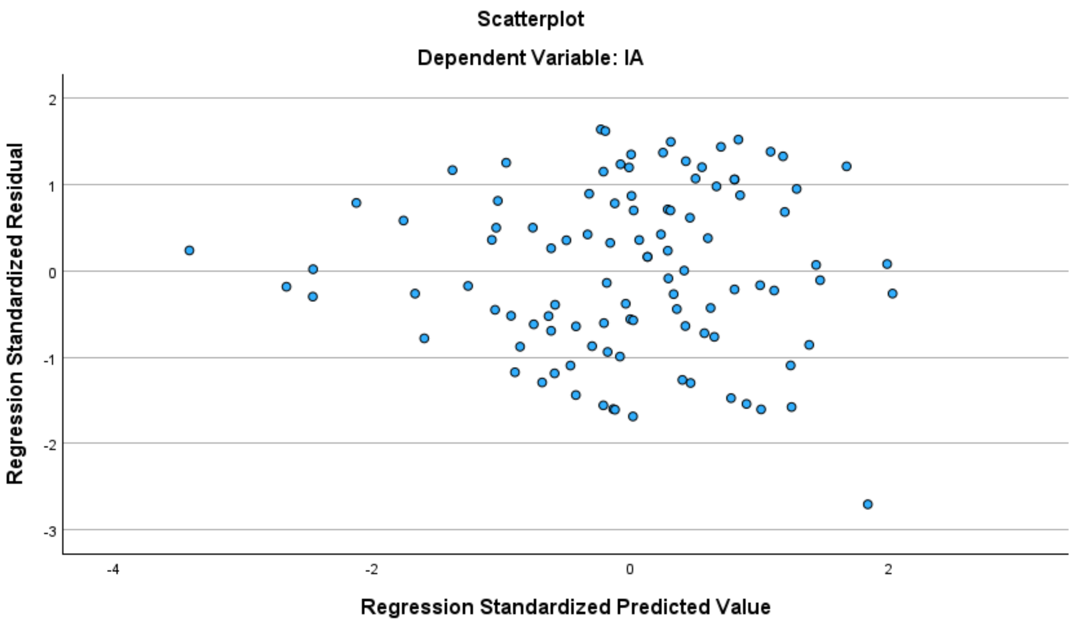


Figure 7: Standardized Residuals vs. Predicted Values

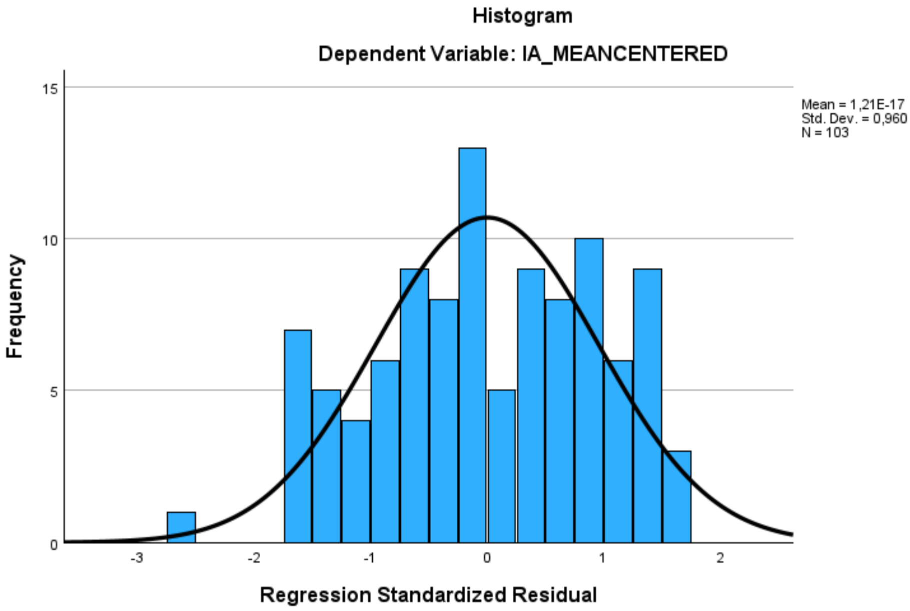


Figure 8: Histogram of Residuals

Total Variance Explained

Factor	Initial Eigenvalues Total	Initial Eigenvalues % of Variance	Initial Eigenvalues Cumulative %	Extraction Sums of Squared Loadings Total	Extraction Sums of Squared Loadings % of Variance	Extraction Sums of Squared Loadings Cumulative %	Rotation Sums of Squared Loadings Total	Rotation Sums of Squared Loadings % of Variance	Rotation Sums of Squared Loadings Cumulative %
1	6,517	46,547	46,547	6,313	45,093	45,093	3,964	28,316	28,316
2	2,799	19,990	66,537	2,549	18,209	63,303	3,529	25,206	53,523
3	2,224	15,887	82,425	2,058	14,701	78,003	3,427	24,481	78,003
4	,540	3,861	86,285						
5	,353	2,520	88,805						
6	,326	2,327	91,132						
7	,304	2,175	93,307						
8	,206	1,470	94,777						
9	,198	1,414	96,191						
10	,169	1,204	97,395						
11	,111	,790	98,185						
12	,095	,679	98,863						
13	,090	,644	99,508						
14	,069	,492	100,000						

Extraction Method: Principal Axis Factoring.

Figure 9: Total Variance Explained from Exploratory Factor Analysis (EFA)

Appendix F: Regression and model testing output

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	,265[a]	,070	,022	1,7309	,070	1,469	5	97	,207
2	,506[b]	,256	,201	1,5650	,185	11,824	2	95	<,001
3	,506[c]	,256	,193	1,5730	,000	,034	1	94	,854

a. Predictors: (Constant), Familiarity with fitness apps and wearables, GENDR_W, Age, Education, Experience with sports and fitness

b. Predictors: (Constant), Familiarity with fitness apps and wearables, GENDR_W, Age, Education, Experience with sports and fitness, PC_MEANCENTERED, AISP_MEANCENTERED

c. Predictors: (Constant), Familiarity with fitness apps and wearables, GENDR_W, Age, Education, Experience with sports and fitness, PC_MEANCENTERED, AISP_MEANCENTERED, INTERACTION

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	3,631	,923		3,936	<,001		
	Age	-,050	,108	-,049	-,467	,642	,871	1,148
	GENDR_W	-,208	,351	-,059	-,591	,556	,954	1,048
	Education	-,057	,163	-,041	-,348	,729	,690	1,448
	Experience with sports and fitness	-,135	,178	-,109	-,755	,452	,459	2,179
	Familiarity with fitness apps and wearables	,327	,132	,310	2,473	,015	,608	1,645
2	(Constant)	3,023	,851		3,552	<,001		
	Age	,017	,100	,016	,167	,868	,831	1,203
	GENDR_W	,232	,330	,066	,702	,485	,881	1,135
	Education	,069	,150	,050	,462	,645	,668	1,497
	Experience with sports and fitness	-,159	,165	-,129	-,968	,336	,439	2,276
	Familiarity with fitness apps and wearables	,255	,122	,242	2,094	,039	,584	1,711
	PC_MEANCENTERED	-,270	,116	-,222	-2,321	,022	,858	1,165
	AISP_MEANCENTERED	,492	,144	,340	3,426	<,001	,796	1,257
3	(Constant)	3,003	,862		3,483	<,001		
	Age	,016	,101	,016	,161	,872	,830	1,204
	GENDR_W	,233	,332	,066	,700	,485	,881	1,135
	Education	,072	,152	,052	,477	,635	,660	1,516
	Experience with sports and fitness	-,158	,166	-,128	-,956	,342	,439	2,279
	Familiarity with fitness apps and wearables	,259	,124	,246	2,088	,040	,572	1,747
	PC_MEANCENTERED	-,270	,117	-,221	-2,306	,023	,858	1,165
	AISP_MEANCENTERED	,481	,158	,332	3,052	,003	,669	1,495
	INTERACTION	,015	,079	,019	,184	,854	,763	1,311

a. Dependent Variable: IA

Figure 10: Hierarchical Regression Coefficients Predicting Intention to Adopt (IA)

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change
1	,265[a]	,070	,022	1,7309	,070	1,469	5	97	,207
2	,649[b]	,422	,386	1,3722	,351	58,327	1	96	<,001

a. Predictors: (Constant), Familiarity with fitness apps and wearables, GENDR_W, Age, Education, Experience with sports and fitness

b. Predictors: (Constant), Familiarity with fitness apps and wearables, GENDR_W, Age, Education, Experience with sports and fitness, PU

Coefficients[a]

Model		Unstandardized Coefficients: B	Std. Error	Standardized Coefficients: Beta	t	Sig.	Collinearity Statistics: Tolerance	VIF
1	(Constant)	3,631	,923		3,936	<,001		
	Age	-,050	,108	-,049	-,467	,642	,871	1,148
	GENDR_W	-,208	,351	-,059	-,591	,556	,954	1,048
	Education	-,057	,163	-,041	-,348	,729	,690	1,448
	Experience with sports and fitness	-,135	,178	-,109	-,755	,452	,459	2,179
	Familiarity with fitness apps and wearables	,327	,132	,310	2,473	,015	,608	1,645
2	(Constant)	-,914	,943		-,970	,335		
	Age	,017	,086	,016	,194	,846	,862	1,160
	GENDR_W	,005	,280	,001	,019	,985	,944	1,059
	Education	,080	,131	,058	,613	,542	,677	1,476
	Experience with sports and fitness	-,089	,141	-,073	-,632	,529	,458	2,183
	Familiarity with fitness apps and wearables	,227	,106	,216	2,148	,034	,599	1,671
	PU	,802	,105	,607	7,637	<,001	,954	1,048

a. Dependent Variable: IA

Figure 11: Regression Results Including Perceived Usefulness (PU) as a Predictor of Intention to Adopt (IA)

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change
1	,265[a]	,070	,022	1,7309	,070	1,469	5	97	,207
2	,437[b]	,191	,140	1,6235	,120	14,251	1	96	<,001

a. Predictors: (Constant), Familiarity with fitness apps and wearables, GENDR_W, Age, Education, Experience with sports and fitness

b. Predictors: (Constant), Familiarity with fitness apps and wearables, GENDR_W, Age, Education, Experience with sports and fitness, DIP

Coefficients[a]

Model		Unstandardized Coefficients: B	Std. Error	Standardized Coefficients: Beta	t	Sig.	Collinearity Statistics: Tolerance	VIF
1	(Constant)	3,631	,923		3,936	<,001		
	Age	-,050	,108	-,049	-,467	,642	,871	1,148
	GENDR_W	-,208	,351	-,059	-,591	,556	,954	1,048
	Education	-,057	,163	-,041	-,348	,729	,690	1,448
	Experience with sports and fitness	-,135	,178	-,109	-,755	,452	,459	2,179
	Familiarity with fitness apps and wearables	,327	,132	,310	2,473	,015	,608	1,645
2	(Constant)	,608	1,179		,516	,607		
	Age	,011	,103	,011	,110	,913	,849	1,178
	GENDR_W	-,194	,329	-,055	-,588	,558	,954	1,048
	Education	,008	,154	,005	,049	,961	,682	1,466
	Experience with sports and fitness	-,085	,168	-,069	-,505	,615	,456	2,193
	Familiarity with fitness apps and wearables	,284	,125	,270	2,284	,025	,603	1,658
	DIP	,502	,133	,354	3,775	<,001	,957	1,045

a. Dependent Variable: IA

Figure 12: Regression Results Including Disclosure Intention (DIP) as a Predictor of Intention to Adopt (IA)