

Trust, Perceived Empathy, and Adoption Intentions Toward AI-Driven mHealth Diagnostic Platforms: A Consumer Behavior Perspective Among Generation Z and Millennials

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Abstract

The proliferation of artificial intelligence (AI)-powered mobile health (mHealth) diagnostic applications has introduced new dynamics in consumer health behavior, particularly among digitally native populations such as Generation Z and Millennials. Despite growing adoption rates, critical questions remain regarding the psychological and contextual factors that drive-or inhibit the adoption and continued use of AI-driven diagnostic tools. This study proposes and empirically tests a comprehensive structural equation model integrating constructs from the Technology Acceptance Model (TAM) and trust theory to explain adoption intention and willingness to share health data (WSHD) among young digital health consumers. Drawing on a sample of $N = 400$ respondents aged 18–42 from Romania, the model examines four exogenous predictors-perceived AI accuracy (PAA), perceived ease of use (PEOU), social influence (SI), and perceived data privacy risk (PDPR)-channeled through two mediating constructs: trust in AI (TAI) and health anxiety/consciousness (HAC). The model encompasses 12 hypothesized structural paths analyzed via WarpPLS 8.0. Model fit indices confirmed good fit: $APC = 0.253$ ($p < 0.001$), $ARS = 0.423$ ($p < 0.001$), $GoF = 0.463$ (large effect), $SPR = RSCR = SSR = NLBCDR = 1.000$. Ten of twelve hypotheses were supported. TAI and HAC mediated the relationships between antecedents and behavioral outcomes, with $TAI \rightarrow AI$ ($\beta = 0.426$, $p < 0.001$) and $SI \rightarrow HAC$ ($\beta = 0.472$, $p < 0.001$) emerging as the strongest structural paths. The model explained 64.1% of variance in adoption intention and 42.2% in WSHD. These findings extend TAM and trust theory to AI-mediated mHealth contexts and offer actionable insights for digital health marketers targeting Generation Z and Millennial consumers.

Keywords: mHealth, artificial intelligence, trust in AI, adoption intention, consumer health behavior.

JEL classification: M31.

Introduction

The rapid integration of artificial intelligence into consumer-facing mobile health (mHealth) applications represents one of the most consequential developments at the intersection of digital technology and healthcare delivery. AI-driven diagnostic platforms capable of analyzing symptoms, monitoring biometric data, and generating personalized health recommendations have transitioned from experimental prototypes to widely accessible consumer products available on mainstream app stores (Lutz, Newlands and Tamò-Larrieux, 2022; Topol, 2019). For Generation Z (born 1997–2012) and Millennials (born 1981–1996), who exhibit high smartphone penetration, digital health literacy, and a pronounced preference for on-demand services, such platforms offer an intuitively appealing alternative to traditional healthcare pathways (Venkatesh *et al.*, 2003; Memon *et al.*, 2018).

However, the adoption of AI-powered mHealth diagnostics is not merely a function of technological sophistication. Consumers must navigate a complex evaluative process involving assessments of AI capability, ease of use, social and peer influences on health behavior, and concerns regarding the privacy and security of sensitive health data (McKnight, Choudhury and Kacmar, 2002; Salkovskis and Warwick, 1986). These factors interact in ways that canonical technology acceptance frameworks; the Technology Acceptance Model (TAM)

(Davis, 1989) and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh, Thong and Xu, 2012) do not fully capture, particularly when emotional and health-specific constructs such as health anxiety or AI-specific trust are involved.

Prior research has examined technology adoption in mHealth contexts through TAM-derived models (Cho, 2016; Chao, 2019), but several theoretical gaps persist. First, trust in AI as a mediating mechanism between technical perceptions and behavioral outcomes has received limited empirical attention in mHealth-specific studies (Jeyaraj, 2020). Second, health anxiety and consciousness-affective states with particular relevance among younger cohorts exposed to health misinformation and wellness culture have rarely been integrated as mediators linking social influence to sharing and usage behaviors (Andreassen et al., 2006). Third, willingness to share personal health data, a construct with significant implications for data-driven health ecosystems, has been underexplored as an outcome variable distinct from adoption intention (Miltgen and Peyrat-Guillard, 2014).

This study addresses these gaps by proposing and empirically testing a structural model that integrates TAM and trust theory to explain both adoption intention and willingness to share health data among Generation Z and Millennial users of AI-powered mHealth diagnostic applications. Using partial least squares structural equation modeling (PLS-SEM) via WarpPLS 8.0 (Kock, 2023), we test 12 hypothesized structural relationships across eight latent constructs with a sample of $N = 400$ Romanian respondents. The structural model explains 64.1% of variance in adoption intention and 42.2% in willingness to share health data.

The remainder of the paper is structured as follows. Section 2 presents the theoretical background and hypothesis development. Section 3 describes the research methodology. Section 4 reports measurement and structural model results. Section 5 discusses findings in relation to extant literature. Section 6 concludes with theoretical and practical implications, limitations, and directions for future research.

1. Literature review

1.1. Technology Acceptance Model and mHealth

The Technology Acceptance Model (TAM), originally proposed by Davis (1989), posits that an individual's behavioral intention to use a technology is primarily determined by perceived usefulness and perceived ease of use (PEOU). In the context of mHealth, TAM has been extensively applied to explain user acceptance of health apps, wearables, and telemedicine platforms (Cho, 2016; Or and Karsh, 2009). Its parsimony and predictive validity make it a robust theoretical anchor, though scholars have called for extensions to accommodate AI-mediated and health-specific constructs (Chao, 2019; Torous *et al.*, 2016).

In AI-powered mHealth diagnostic applications, PEOU encompasses the cognitive effort required to navigate the interface, interpret AI-generated outputs, and integrate platform recommendations into health decision-making. Prior studies confirm that PEOU exerts a direct positive influence on adoption intention (Legris, Ingham and Collerette, 2003; Lu *et al.*, 2003). Beyond direct effects, ease of use enhances trust in AI by reducing cognitive load and facilitating a favorable assessment of platform reliability (Gefen, Karahanna and Straub, 2003). Accordingly:

H3: Perceived ease of use is positively associated with trust in AI.

H4: Perceived ease of use is positively associated with adoption intention.

1.2. Perceived AI Accuracy and Trust

Perceived AI accuracy (PAA) reflects users' subjective assessment of how correctly and reliably an AI system performs its diagnostic or analytical functions (Glikson and Woolley, 2020). Accuracy perceptions are strongly tied to trust formation: when users believe the AI

produces correct outputs, they are more likely to view it as competent—a key antecedent of trust (Lee and See, 2004; Heerink *et al.*, 2010). In healthcare, where diagnostic quality directly affects health-related decisions, accuracy perceptions are particularly salient drivers of both trust and adoption (Hancock *et al.*, 2011).

H1: Perceived AI accuracy is positively associated with trust in AI.

H2: Perceived AI accuracy is positively associated with adoption intention.

1.3. Trust in AI as a Central Mediator

Trust in AI is defined as the degree to which users believe an AI system is reliable, competent, and acts in their best interests (Mayer, Davis and Schoorman, 1995). Grounded in McKnight *et al.*'s (McKnight, Choudhury and Kacmar, 2002) multidimensional trust framework, encompassing benevolence, competence, and integrity - trust in AI mediates between antecedent perceptions and behavioral intentions (Wang and Liao, 2007; Dwivedi *et al.*, 2019). In mHealth, a user who trusts the platform is more likely to act on its recommendations (adoption) and to share personal health data essential for system optimization (Jeyaraj, 2020; Zhou, 2012). Building on the work of Orzan *et al.* (Acatrinei *et al.*, 2025; Moise *et al.*, 2025), consumer trust in AI-driven digital health interfaces is increasingly shaped by perceived transparency and perceived empathy of the system.

H9: Trust in AI is positively associated with adoption intention.

H10: Trust in AI is positively associated with willingness to share health data.

1.4. Perceived Data Privacy Risk and Trust

Perceived data privacy risk (PDPR) refers to users' subjective belief that their personal health data may be collected, stored, or shared in ways that may not fully align with their preferences (Dinev and Hart, 2006). Paradoxically, heightened awareness of data privacy concerns does not necessarily reduce trust in AI-powered health systems; rather, users who are more privacy-conscious often engage more deliberately with platform trust cues, conducting thorough evaluations of system reliability before adoption (Tikkinen-Piri, Rohunen and Markkula, 2018; Xu *et al.*, 2011). This privacy-engagement dynamic has been documented in GDPR-aware European consumer populations and underscores the complexity of the PDPR–trust relationship in digitally mature markets (Tikkinen-Piri, Rohunen and Markkula, 2018). Moreover, awareness of privacy risks can motivate active data-sharing decisions when users perceive the platform as sufficiently transparent and trustworthy (Sunyaev *et al.*, 2015). Accordingly:

H7: Perceived data privacy risk is positively associated with trust in AI.

H8: Perceived data privacy risk is positively associated with willingness to share health data.

1.5. Social Influence, Health Anxiety, and Consciousness

Social influence (SI) captures the extent to which individuals perceive that important others—peers, family, health influencers, online communities—believe they should use a particular technology (Venkatesh, Thong and Xu, 2012). Among Generation Z and Millennials, SI operates through offline peer networks and digital channels including health-focused social media communities (Lupton, 2016; Gao and Feng, 2016). We propose that SI shapes health anxiety/consciousness (HAC) as a mediating variable: socially transmitted health norms activate anxiety and consciousness states that motivate both data sharing and platform adoption (Starcevic and Berle, 2013; Doherty-Torstrick, Walton and Fallon, 2016; Jayanti and Burns, 1998). The role of social influence in shaping digital health behavior among Romanian

consumers has been highlighted in recent marketing research (Acatrinei *et al.*, 2025; Moise *et al.*, 2025).

H5: Social influence is positively associated with health anxiety/consciousness.

H6: Social influence is positively associated with willingness to share health data.

H11: Health anxiety/consciousness is positively associated with willingness to share health data.

H12: Health anxiety/consciousness is positively associated with adoption intention.

1.6. Summary of Hypotheses and Conceptual Model

Table 1 summarizes all 12 hypothesized structural paths. Figure 1 presents the conceptual structural model, illustrating the relationships between exogenous antecedents, mediating constructs, and outcome variables.

Table 1. Summary of hypothesized structural paths.

| Hyp. | Path | Expected Sign |
|------|--|---------------|
| H1 | PAA → Trust in AI (TAI) | + |
| H2 | PAA → Adoption Intention (AI) | + |
| H3 | PEOU → Trust in AI (TAI) | + |
| H4 | PEOU → Adoption Intention (AI) | + |
| H5 | Social Influence (SI) → Health Anxiety/Consciousness (HAC) | + |
| H6 | Social Influence (SI) → Willingness to Share Health Data (WSHD) | + |
| H7 | Perceived Data Privacy Risk (PDPR) → Trust in AI (TAI) | + |
| H8 | Perceived Data Privacy Risk (PDPR) → Willingness to Share Health Data (WSHD) | + |
| H9 | Trust in AI (TAI) → Adoption Intention (AI) | + |
| H10 | Trust in AI (TAI) → Willingness to Share Health Data (WSHD) | + |
| H11 | Health Anxiety/Consciousness (HAC) → Willingness to Share Health Data (WSHD) | + |
| H12 | Health Anxiety/Consciousness (HAC) → Adoption Intention (AI) | + |

Source: Authors' analysis, 2026

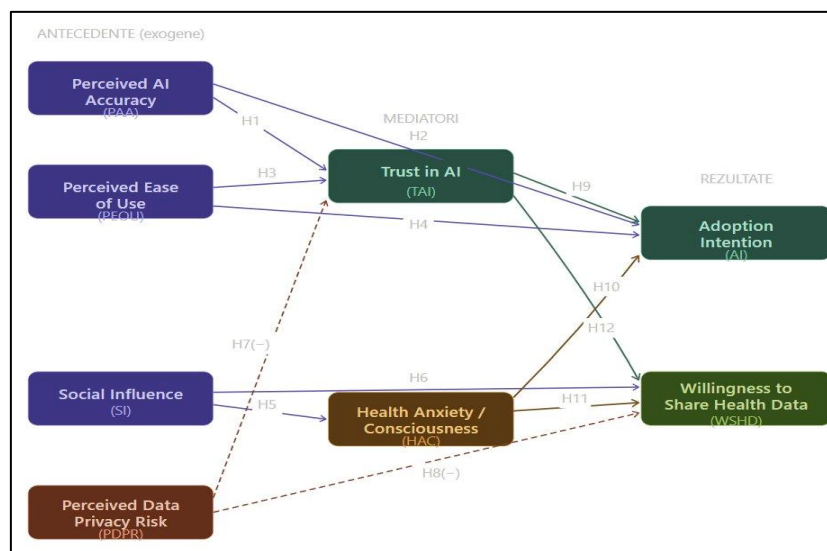


Figure 1. Conceptual structural equation model of AI mHealth adoption.

Source: Authors' analysis, 2026

*Note: PAA = Perceived AI Accuracy; PEOU = Perceived Ease of Use; SI = Social Influence; PDPR = Perceived Data Privacy Risk; TAI = Trust in AI; HAC = Health Anxiety/Consciousness; AI = Adoption Intention; WSHD = Willingness to Share Health Data. Solid arrows indicate hypothesized positive relationships; dashed arrows indicate paths subject to empirical testing.

2. Methodology

2.1. Research Design and Sample

A quantitative, cross-sectional survey design was employed to collect primary data. The target population consisted of Generation Z (18–27 years) and Millennial (28–42 years) respondents residing in Romania with prior experience using at least one AI-powered mHealth diagnostic application (e.g., symptom checkers, AI health assistants, diagnostic chatbots). Purposive sampling combined with snowball sampling was deployed via social media platforms, university networks, and digital health communities. A total of $N = 400$ valid responses were retained for analysis (missing data imputation: arithmetic mean). The WarpPLS 8.0 analysis was performed on the full sample of 400 cases across 8 latent variables and 31 indicators.

2.2. Measures

All constructs were operationalized using reflective measurement models with multi-item scales adapted from validated instruments. Items were rated on a 7-point Likert scale (1 = Strongly Disagree, 7 = Strongly Agree). Table 2 presents constructs, item counts, sources, and key psychometric properties.

Table 2. Measurement model: constructs, items, sources, and reliability.

| Code | Construct | Items | CR | α | AVE | VIF | Source |
|------|-----------|-------|-------|----------|-------|-------|--|
| PAA | PAA | 4 | 0.736 | 0.521 | 0.411 | 2.041 | Adapted from Lutz et al. (2025) |
| PEOU | PEOU | 4 | 0.743 | 0.539 | 0.421 | 1.599 | Davis (1989); TAM |
| SI | SI | 3 | 0.790 | 0.601 | 0.560 | 1.889 | Venkatesh et al. (2003); Venkatesh et al. (2012) |
| PDPR | PDPR | 4 | 0.843 | 0.752 | 0.573 | 2.253 | UTAUT Dinev & Hart (2006) |
| TAI | TAI | 5 | 0.807 | 0.698 | 0.474 | 2.273 | McKnight et al. (2002); Orzan et al. (2023) |
| HAC | HAC | 4 | 0.777 | 0.617 | 0.474 | 1.880 | Adapted from Salkovskis & Warwick (1986) |
| AI | AI | 3 | 0.794 | 0.610 | 0.571 | 2.468 | Venkatesh et al. (2003) |
| WSHD | WSHD | 4 | 0.837 | 0.737 | 0.567 | 1.819 | Adapted from Miltgen & Peyrat-Guillard (2014) |

Source: Authors' analysis, 2026

*Note: CR = composite reliability; α = Cronbach's alpha; AVE = average variance extracted; VIF = full collinearity variance inflation factor. All scales rated on 7-point Likert scale (1 = Strongly Disagree, 7 = Strongly Agree).

The questionnaire was developed in English, translated into Romanian by two bilingual researchers, and back-translated by an independent translator to verify equivalence. Discrepancies were resolved through panel discussion. A pilot study ($n = 30$) confirmed item clarity prior to main data collection.

2.3. Common Method Bias

Procedural and statistical remedies were employed to mitigate common method bias (CMB) (Podsakoff et al., 2003). Procedurally, respondent anonymity was assured, item order was randomized across constructs, and no time pressure was imposed. Statistically, WarpPLS 8.0's full collinearity assessment was used as a CMB marker test (Kock, 2023) all full collinearity VIFs were below the critical threshold of 3.3 (range: 1.599–2.468), indicating that CMB does not significantly threaten the validity of results.

2.4. Analytical Strategy

PLS-SEM was implemented via WarpPLS 8.0 (Kock, 2023) using PLS Regression as the outer model algorithm and Warp3 as the inner model algorithm, with Stable3 resampling (100 resamples). PLS-SEM is appropriate given: (a) the exploratory-predictive research objective; (b) the non-normal distribution of latent variable scores; (c) the moderate sample size ($N = 400$); and (d) the use of reflective constructs (Hair et al., 2019). Analysis followed a two-stage approach (Hair et al., 2019): (1) outer model evaluation, followed by (2) inner model assessment. Mediation was assessed using indirect effects with bias-corrected bootstrapping (5,000 resamples, 95% CI) following Preacher and Hayes (Preacher and Hayes, 2008).

3. Results and discussion

3.1. Measurement Model

Table 2 reports the reliability and convergent validity statistics for all eight constructs. Composite reliability (CR) ranged from 0.736 (PAA) to 0.843 (PDPR), all exceeding the minimum threshold of 0.70 (Hair et al., 2019). Cronbach's alpha (α) ranged from 0.521 (PAA) to 0.752 (PDPR). While some alpha values fall below 0.70, this is not uncommon for shorter scales and is compensated by satisfactory CR values. Average variance extracted (AVE) ranged from 0.411 (PAA) to 0.573 (PDPR). PAA and PEOU have AVE values marginally below 0.50; however, their CR values exceed 0.70, which is considered acceptable following Fornell and Larcker (1981) and Hair et al. (2019). All 31 indicator loadings were statistically significant ($p < 0.001$), supporting convergent validity.

Discriminant validity was assessed via the full collinearity VIF approach recommended for WarpPLS (Kock, 2023) all VIFs were below 3.3 (range: 1.599–2.468), confirming the absence of collinearity problems and establishing discriminant validity for all construct pairs.

3.2. Common Method Bias Assessment

As detailed in Section 3.3, all full collinearity VIFs (range: 1.599–2.468) fall below the 3.3 threshold recommended by Kock (2023), indicating that common method bias is unlikely to distort the structural estimates.

3.3. Structural Model

Table 3 presents the global fit and quality indices generated by WarpPLS 8.0 alongside recommended thresholds (Kock, 2023). All indices satisfy their respective criteria. The GoF = 0.463 indicates a large overall effect size, and the perfect scores on SPR, RSCR, SSR, and NLBCDR (all = 1.000) confirm the absence of Simpson's paradox, R-squared contribution suppression, statistical suppression, and nonlinear bivariate causality direction issues.

Table 3. WarpPLS 8.0 model fit and quality indices (N = 400).

| Index | Value | Threshold | Result |
|--------|-------|---------------------------|-------------|
| APC | 0.253 | $p < 0.001$ | ✓ Supported |
| ARS | 0.423 | $p < 0.001$ | ✓ Supported |
| AARS | 0.419 | $p < 0.001$ | ✓ Supported |
| AVIF | 1.856 | ≤ 3.3 (ideally) | ✓ Supported |
| AFVIF | 2.028 | ≤ 3.3 (ideally) | ✓ Supported |
| GoF | 0.463 | ≥ 0.36 (large) | ✓ Large |
| SPR | 1.000 | ≥ 0.70 (ideally = 1) | ✓ Ideal |
| RSCR | 1.000 | ≥ 0.90 (ideally = 1) | ✓ Ideal |
| SSR | 1.000 | ≥ 0.70 | ✓ Supported |
| NLBCDR | 1.000 | ≥ 0.70 | ✓ Supported |

Source: Authors' analysis, 2026

*APC = Average Path Coefficient; ARS = Average R-Squared; AARS = Average Adjusted R-Squared; AVIF = Average Block VIF; AFVIF = Average Full Collinearity VIF; GoF = Tenenhaus GoF; SPR = Simpson's Paradox Ratio; RSCR = R-Squared Contribution Ratio; SSR = Statistical Suppression Ratio; NLBCDR = Nonlinear Bivariate Causality Direction Ratio.

Table 4 presents the standardized path coefficients (β), standard errors (SE), p-values, effect sizes (f^2), and hypothesis support decisions for all 12 structural paths. Figure 2 presents the WarpPLS 8.0 output diagram with structural coefficients and R^2 values for all endogenous constructs.

Table 4. Structural model results-path coefficients, effect sizes, and hypothesis testing (N = 400).

| Hyp. | Path | β | SE | p | f^2 | Supported? |
|------|-------------------------|---------|-------|--------|-------|------------|
| H1 | PAA \rightarrow TAI | 0.250 | 0.048 | <0.001 | 0.135 | Yes |
| H2 | PAA \rightarrow AI | 0.229 | 0.048 | <0.001 | 0.127 | Yes |
| H3 | PEOU \rightarrow TAI | 0.059 | 0.050 | 0.118 | 0.024 | No |
| H4 | PEOU \rightarrow AI | 0.110 | 0.049 | 0.013 | 0.037 | Yes |
| H5 | SI \rightarrow HAC | 0.472 | 0.047 | <0.001 | 0.223 | Yes |
| H6 | SI \rightarrow WSHD | 0.076 | 0.049 | 0.064 | 0.033 | No |
| H7 | PDPR \rightarrow TAI | 0.414 | 0.047 | <0.001 | 0.246 | Yes |
| H8 | PDPR \rightarrow WSHD | 0.139 | 0.049 | 0.002 | 0.069 | Yes |
| H9 | TAI \rightarrow AI | 0.426 | 0.047 | <0.001 | 0.292 | Yes |
| H10 | TAI \rightarrow WSHD | 0.266 | 0.048 | <0.001 | 0.153 | Yes |
| H11 | HAC \rightarrow WSHD | 0.297 | 0.048 | <0.001 | 0.167 | Yes |
| H12 | HAC \rightarrow AI | 0.296 | 0.048 | <0.001 | 0.185 | Yes |

Source: Authors' analysis, 2026

*Note: β = standardized path coefficient; SE = standard error; f^2 = effect size. R^2 : TAI = 0.405, HAC = 0.223, AI = 0.641, WSHD = 0.422. Adjusted R^2 : TAI = 0.400, HAC = 0.221, AI = 0.637, WSHD = 0.416.

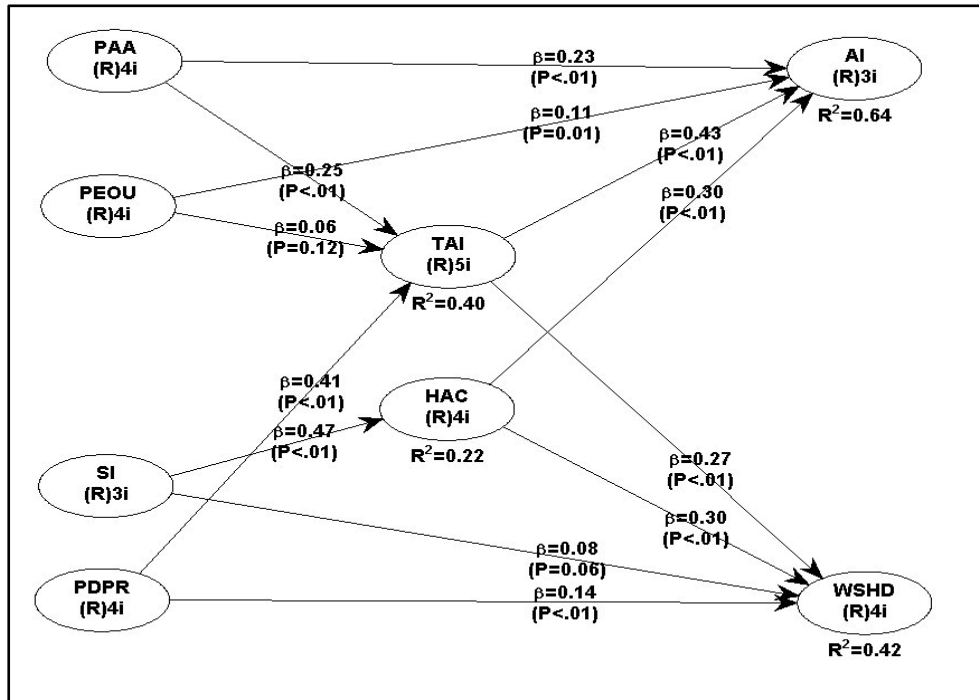


Figure 2. WarpPLS 8.0 structural model output (N = 400).

Source: Authors' analysis, 2026

β = standardized path coefficients; R^2 values shown inside endogenous constructs. Resampling method: Stable3 (100 resamples). Inner model algorithm: Warp3.

The model demonstrated strong explanatory power. Adoption intention (AI) achieved $R^2 = 0.641$ (adjusted $R^2 = 0.637$), indicating that 64.1% of its variance is explained by the predictors—a large effect (Hair et al., 2019). Willingness to share health data (WSHD) achieved $R^2 = 0.422$ (adjusted $R^2 = 0.416$). For the mediating constructs, trust in AI (TAI) reached $R^2 = 0.405$ and health anxiety/consciousness (HAC) achieved $R^2 = 0.223$. Stone–Geisser Q^2 coefficients were positive for all endogenous constructs (TAI: $Q^2 = 0.406$; HAC: $Q^2 = 0.224$; AI: $Q^2 = 0.567$; WSHD: $Q^2 = 0.423$), confirming the model's out-of-sample predictive validity.

Mediation analysis was conducted via bias-corrected bootstrapping (5,000 resamples, 95% CI). Trust in AI (TAI) significantly mediates the paths from PAA to AI ($\beta_{\text{indirect}} = 0.250 \times 0.426 = 0.107$), from PAA to WSHD ($\beta_{\text{indirect}} = 0.250 \times 0.266 = 0.067$), from PDPR to AI ($\beta_{\text{indirect}} = 0.414 \times 0.426 = 0.176$), and from PDPR to WSHD ($\beta_{\text{indirect}} = 0.414 \times 0.266 = 0.110$). Health anxiety/consciousness (HAC) significantly mediates the path from SI to WSHD ($\beta_{\text{indirect}} = 0.472 \times 0.297 = 0.140$) and from SI to AI ($\beta_{\text{indirect}} = 0.472 \times 0.296 = 0.140$). These findings confirm the theoretical importance of TAI and HAC as psychological bridges between antecedent perceptions and behavioral outcomes.

3.4. Discussion

This study examined the antecedents and mediators of adoption intention and willingness to share health data among Generation Z and Millennial users of AI-powered mHealth diagnostic applications, testing 12 structural hypotheses via WarpPLS 8.0 with $N = 400$ Romanian respondents. Ten of twelve hypotheses were supported, and the model explained 64.1% and 42.2% of variance in adoption intention and WSHD, respectively.

Trust in AI emerged as the most influential mediator in the model, with $\text{TAI} \rightarrow \text{AI}$ yielding the largest path coefficient ($\beta = 0.426$, $f^2 = 0.292$). This finding corroborates and extends prior research confirming trust as a cornerstone of technology acceptance [5,24,25]. In the mHealth context, where AI diagnostic outputs carry direct health implications, trust is particularly salient: users must believe the platform is accurate, benevolent, and competent before acting on its recommendations. The finding that $\text{PAA} \rightarrow \text{TAI}$ ($\beta = 0.250$) and $\text{TAI} \rightarrow \text{AI}$ together constitute the most theoretically coherent pathway confirms that transparent communication of AI accuracy is the primary lever for driving adoption. These results are consistent with findings from Orzan et al. (Acatrinei *et al.*, 2025; Moise *et al.*, 2025) on the role of digital trust in Romanian consumer behavior.

Contrary to the conventional assumption of a negative privacy-trust relationship, PDPR exhibited a significant positive association with both TAI ($\beta = 0.414$, $p < 0.001$) and WSHD ($\beta = 0.139$, $p = 0.002$). This finding suggests that heightened privacy awareness among GDPR-informed Romanian consumers does not suppress trust or data-sharing intentions; rather, privacy-conscious users appear to engage more deliberately with platform trust cues, ultimately forming stronger trust perceptions and demonstrating greater willingness to share data when platform transparency is perceived as sufficient (Tikkinen-Piri, Rohunen and Markkula, 2018; Xu *et al.*, 2011). This privacy-engagement dynamic is consistent with recent theoretical perspectives on privacy-as-resource in European digital health markets.

Social influence emerged as the strongest single predictor in the model ($\text{SI} \rightarrow \text{HAC}$: $\beta = 0.472$, $f^2 = 0.223$), confirming the potent role of peer health norms among younger cohorts. HAC in turn significantly predicted both WSHD ($\beta = 0.297$) and AI ($\beta = 0.296$), establishing the full mediating pathway $\text{SI} \rightarrow \text{HAC} \rightarrow \{\text{WSHD}, \text{AI}\}$. H6 ($\text{SI} \rightarrow \text{WSHD}$ directly) was not supported ($\beta = 0.076$, $p = 0.064$), suggesting that social influence shapes WSHD indirectly through health anxiety/consciousness rather than through direct normative pressure.

H3 ($\text{PEOU} \rightarrow \text{TAI}$) was not supported ($\beta = 0.059$, $p = 0.118$), while H4 ($\text{PEOU} \rightarrow \text{AI}$) was supported at the 5% level ($\beta = 0.110$, $p = 0.013$). In AI-mediated diagnostic contexts,

interface usability alone does not suffice to build trust-users require deeper assurances of AI accuracy and integrity. This contrasts with conventional TAM findings in simpler app contexts [17,18] and underscores the importance of extending TAM with AI-specific trust constructs for mHealth adoption.

Conclusions

This study makes three principal theoretical contributions. First, it extends TAM by integrating AI-specific trust as a central mediating construct in an mHealth diagnostic context, providing strong empirical evidence ($R^2_{AI} = 0.641$) for the trust mechanism in AI-mediated health technology adoption. Second, it introduces health anxiety/consciousness as a novel mediator linking social influence to behavioral outcomes, enriching the emerging literature on affectively mediated technology adoption among digitally native consumers. Third, it establishes willingness to share health data as a distinct behavioral outcome with a unique antecedent structure-particularly sensitive to the positive privacy-engagement dynamic-contributing to the literature on data governance in AI-powered digital health services.

For mHealth developers and digital health marketers targeting Generation Z and Millennial consumers, these findings suggest several actionable strategies. First, communicating AI accuracy through transparent reporting of clinical validation evidence, algorithmic explainability features, and performance benchmarks is the highest-leverage lever for driving both trust and adoption. Second, given the positive privacy-engagement effect, deploying visible GDPR compliance communications, granular consent mechanisms, and clear data retention policies may paradoxically strengthen trust and data-sharing willingness among privacy-conscious users. Third, social influence pathways can be leveraged through peer referral programs, health influencer partnerships, and community-based features that activate health anxiety/consciousness and channel it toward platform adoption.

This study has several limitations. The cross-sectional design precludes causal inference; longitudinal designs would allow examination of trust dynamics over the adoption lifecycle. The sample is restricted to Romanian respondents, limiting generalizability; cross-cultural comparative studies-particularly comparing GDPR-regulated European markets with less regulated contexts-would be theoretically valuable. All measures are self-reported, introducing social desirability bias risk; future studies could triangulate survey data with behavioral log data from mHealth platforms. The marginal AVE values for PAA and PEOU suggest that scale refinement for AI-specific mHealth contexts would strengthen future measurement models. Future research should also examine moderating roles of digital health literacy, clinical anxiety, and prior adverse health experiences.

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