

# A Social Influence Perspective on Technology Adoption: The Roles of Social Acceptability and Behavioural Intentions

Jenny Twyford

Thompson Rivers University

Russell Currie

Thompson Rivers University

Matti Haverila

[haverila@gmail.com](mailto:haverila@gmail.com)

Thompson Rivers University

---

## Article

**Keywords:** Genetic testing, Social norms, Social acceptability, Behavioural intentions, Actual usage of genetic testing, PLS-SEM

**Posted Date:** October 18th, 2026

**DOI:** <https://doi.org/10.21203/rs.3.rs-10540693/v1>

**License:**   This work is licensed under a Creative Commons Attribution 4.0 International License.  
[Read Full License](#)

**Additional Declarations:** No competing interests reported.

---

# Abstract

## Background

Successful implementation of precision medicine depends not only on the availability of genetic testing (GT) services but also on patients' willingness to use them. This study examined how social influence mechanisms shape GT uptake by investigating the roles of subjective norms, social acceptability, and behavioural intentions.

## Methods

A cross-sectional online survey was conducted among 833 adults. After data screening, 808 responses were retained for analysis. Partial least squares structural equation modelling (PLS-SEM) was used to examine direct and indirect relationships among subjective norms, social acceptability, behavioural intentions, and actual GT use.

## Results

Subjective norms exerted strong positive effects on both social acceptability and behavioural intentions. Social acceptability positively influenced behavioural intentions, which emerged as the strongest predictor of actual GT use. All hypothesized indirect effects were statistically significant, demonstrating that subjective norms influence GT uptake through sequential mediation involving social acceptability and behavioural intentions.

## Conclusions

Social acceptability represents an important behavioural mechanism linking social influence with actual genetic testing uptake. These findings extend understanding of the behavioural processes underlying patient engagement with precision medicine and suggest that implementation strategies should address social legitimacy alongside service accessibility to improve uptake of genetic testing and other emerging health technologies.

## Introduction

The successful implementation of innovative healthcare technologies remains a major challenge for health systems worldwide. Although advances in precision medicine have expanded opportunities for disease prevention, early diagnosis, personalized treatment, and risk stratification, many evidence-based innovations continue to experience slower-than-expected uptake in routine clinical practice (Damschroder et al., 2022; Johnson et al., 2021). Improving the implementation of these innovations requires more than technological capability or clinical effectiveness; it also depends on understanding

the behavioural and social processes that influence whether individuals choose to engage with new healthcare services (Nilsen, 2015). Consequently, identifying factors that facilitate patient uptake has become an important priority in health services research.

Genetic testing (GT) represents a particularly relevant example of these implementation challenges. Recent advances in genomic medicine have substantially increased the accessibility and clinical utility of GT for disease prevention, diagnosis, pharmacogenomics, reproductive decision-making, and personalized treatment planning (Johnson et al., 2021). Clinical applications of GT continue to expand as healthcare systems increasingly integrate precision medicine into routine care. Despite these advances, uptake remains below expectations in many populations, suggesting that the availability of testing alone is insufficient to ensure widespread adoption (Henneman et al., 2013; Ho & Lin, 2025). This implementation gap highlights the need to better understand the behavioural mechanisms that influence individuals' willingness to utilize genetic testing services.

Research on health technology adoption has traditionally relied on established behavioural theories such as the Theory of Planned Behaviour (TPB) (Ajzen, 1991, 2011), the Technology Acceptance Model (TAM) (Davis, 1989), the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003), and Diffusion of Innovations (DOI) (Rogers, 2003). Collectively, these frameworks have demonstrated that behavioural intentions are among the strongest predictors of actual behaviour and that perceptions of usefulness, ease of use, and subjective norms play important roles in shaping adoption decisions (Holden & Karsh, 2010; J. W. Lee, 2024; Rahimi et al., 2018). Within healthcare, these models have been widely applied to explain the adoption of digital health technologies, electronic health services, mobile health applications, and genetic testing (Holden & Karsh, 2010; Rahimi et al., 2018; Zhang et al., 2025).

Among these determinants, social influence has received increasing attention because healthcare decisions are rarely made in isolation. Individuals frequently rely on recommendations from family members, healthcare professionals, peers, and broader social networks when considering preventive health behaviours and emerging medical technologies (Ajzen, 1991; Henneman et al., 2013; Oliveri et al., 2016). In the context of GT, social influence may be particularly important because decisions often involve ethical considerations, privacy concerns, uncertainty regarding future health outcomes, and implications for family members. Consequently, perceptions of social approval may substantially affect whether individuals are willing to engage with genetic testing.

However, existing behavioural models may not fully explain how social influence translates into actual healthcare utilization. Subjective norms capture perceived expectations from important others but do not necessarily reflect whether individuals perceive a healthcare intervention as socially legitimate, ethically appropriate, or broadly accepted within society. These broader perceptions are captured by the concept of social acceptability, which refers to the extent to which an innovation is considered appropriate, legitimate, and acceptable within its wider social and institutional context (Gordon et al., 2022; Wutz et al., 2023). Although social acceptability has attracted growing attention in studies of

emerging healthcare technologies and artificial intelligence, its role within behavioural models of genetic testing adoption remains largely unexplored (Hassan et al., 2024; Wutz et al., 2023).

This represents an important gap in the literature. Existing studies of GT adoption have primarily examined the direct effects of attitudes, perceived usefulness, trust, subjective norms, and behavioural intentions (Henneman et al., 2013; Ho & Lin, 2025a; Oliveri et al., 2016; Rahimi et al., 2018).

Comparatively little research has investigated the mechanisms through which subjective norms become translated into actual healthcare behaviour. Understanding these mechanisms is important because implementation of precision medicine depends not only on positive attitudes towards genetic testing but also on whether individuals perceive the technology as socially acceptable and appropriate for themselves and their communities. Examining these intermediary processes may therefore provide a more comprehensive explanation of healthcare utilization than models focusing solely on direct relationships.

Accordingly, this study develops and empirically tests a behavioural model integrating subjective norms, social acceptability, behavioural intentions, and actual use of genetic testing. Specifically, the objectives of this study are to: (1) examine the influence of subjective norms on perceptions of social acceptability and behavioural intentions; (2) investigate whether social acceptability contributes to behavioural intentions beyond traditional normative influences; and (3) evaluate the direct and indirect pathways through which social influence affects actual utilization of genetic testing.

This study contributes to health services research in several important ways. First, it extends existing behavioural models by introducing social acceptability as a distinct intermediary mechanism linking subjective norms with behavioural intentions and healthcare utilization. Second, it provides empirical evidence supporting a sequential behavioural pathway through which social influence contributes to the implementation of precision medicine. Third, by examining actual use rather than behavioural intentions alone, the study contributes to the growing literature addressing the intention–behaviour gap in healthcare adoption (Ruyobeza et al., 2025; Sheeran & Webb, 2016). Collectively, these findings contribute to a more comprehensive understanding of the behavioural mechanisms underlying the uptake of innovative healthcare technologies.

The findings also have practical relevance for healthcare providers, health system managers, and policymakers responsible for implementing precision medicine initiatives. Identifying how perceptions of social acceptability influence patient behaviour may inform communication strategies, community engagement initiatives, and implementation interventions designed to increase the uptake of genetic testing and other emerging healthcare technologies. As healthcare systems continue to expand access to precision medicine, understanding the behavioural determinants of patient participation will become increasingly important for achieving successful implementation and improving population health outcomes.

The remainder of this paper is organized as follows. The next section reviews the relevant literature and develops the study hypotheses. The methodology and analytical procedures are then described, followed

by presentation of the empirical findings. Finally, the results are discussed in relation to existing theory and health services research, and implications for healthcare practice and future research are presented.

## Literature review and hypotheses development

### *Genetic testing (GT) as an implementation of precision medicine context*

GT has emerged as a critical component of precision medicine, enabling individuals to assess genetic predispositions, personalize treatment strategies, and engage in preventive healthcare behaviours (Ho & Lin, 2025b; Johnson et al., 2021b). Despite its growing availability and demonstrated benefits, adoption remains uneven due to concerns related to privacy, ethics, accessibility, and trust (Dhagarra et al., 2020; Hassan et al., 2024). These factors play a role in adoption, as they relate to the technology's individual behavioural and social acceptability. Consequently, understanding the behavioural and social drivers of GT adoption has become an important research priority.

### *The role of subjective norms in genetic testing*

Subjective norms refer to an individual's perception of social pressure to perform or not perform a behaviour. Prior research has consistently shown that subjective norms significantly influence behavioural intentions in healthcare and technology adoption contexts (Ajzen, 1991; Lee et al., 2025; Rahimi et al., 2018). In GT, perceptions of approval from family, peers, and society can shape attitudes and decision-making, thereby influencing overall uptake (Henneman et al., 2013; Oliveri et al., 2016). However, subjective norms alone may not fully capture whether a behaviour is perceived as socially legitimate or acceptable.

### *Social acceptability in genetic testing*

Social acceptability reflects the extent to which a behaviour is perceived as appropriate, ethical, and supported within a societal context (Gordon et al., 2022; Wutz et al., 2023). Unlike subjective norms, which focus on perceived expectations, social acceptability captures broader societal endorsement and institutional legitimacy. In sensitive domains such as GT, where ethical and privacy concerns are prominent, social acceptability plays a crucial role in shaping adoption decisions (Alelyani, 2025; Dhagarra et al., 2020). Social influence is therefore proposed to indirectly influence social acceptability, suggesting that favourable norms increase acceptance, which in turn facilitates adoption. Thus, we propose the first hypothesis.

*Hypothesis 1: Subjective norms have a significant positive effect on the social acceptability of GT.*

### *Behavioural intentions*

Behavioural intentions represent an individual's readiness or willingness to perform a specific behaviour and are a central predictor of actual behaviour in both TPB and TAM (Davis, 1989b; Holden & Karsh, 2010). In healthcare contexts, behavioural intentions have been widely shown to influence the adoption

of digital health technologies and preventive health behaviours (Rahimi et al., 2018; Zhang et al., 2025). Social acceptability is expected to enhance behavioural intentions by reinforcing the perceived legitimacy and desirability of GT, while subjective norms may also exert a direct influence. Thus, we present the second and third hypotheses.

*Hypothesis 2: Social acceptability has a significant positive effect on behavioural intentions towards GT.*

*Hypothesis 3: Subjective norms have a significant positive effect on behavioural intentions towards GT.*

#### *Actual usage of genetic testing*

Actual usage refers to the extent to which individuals engage in GT behaviours, including undergoing testing and recommending it to others. While behavioural intentions are a strong predictor of behaviour, prior research highlights an intention–behaviour gap, particularly in healthcare (Ruyobeza et al., 2025; Sheeran & Webb, 2016). This gap underscores the importance of examining not only intentions but also actual usage outcomes. Consistent with behavioural theory, stronger intentions are expected to translate into higher levels of actual adoption. Thus, we present the fourth hypothesis.

*Hypothesis 4: Behavioural intentions towards GT have a significant positive effect on actual usage of GT.*

#### *Hypothesis setting for the indirect effects*

Beyond direct relationships, the model incorporates several indirect (mediating) effects to capture the underlying mechanisms through which social influence translates into behaviour. Mediation analysis is widely recognized as essential for understanding causal processes in behavioural research, as it explains how and why relationships occur rather than merely identifying their existence (Baron & Kenny, 1986; Hair et al., 2022; Preacher & Hayes, 2008). In line with TPB, behavioural intentions are expected to mediate the relationship between antecedents and actual behaviour, reflecting the central role of intention formation in decision-making processes (Ajzen, 1991; Fishbein & Ajzen, 2011). Furthermore, prior research highlights that social influences often operate through sequential mechanisms, where perceptions of social approval shape broader acceptance, which in turn drives intentions and subsequent behaviour (A. T. Lee et al., 2025; Rahimi et al., 2018). This aligns with the well-documented intention–behaviour gap, suggesting that multiple mediating stages are required to translate favourable perceptions into actual usage (Ruyobeza et al., 2025; Sheeran & Webb, 2016). Accordingly, this study proposes a series of indirect effects in which behavioural intentions mediate the relationship between social acceptability and actual usage, while subjective norms exert indirect effects through both social acceptability and behavioural intentions, forming a sequential mediation pathway.

*Hypothesis 5: Behavioural intentions mediate the relationship between social acceptability and actual usage of GT.*

*Hypothesis 6: Social acceptability and behavioural intentions mediate the relationship between subjective norms and actual usage of GT.*

*Hypothesis 7: Behavioural intentions mediate the relationship between subjective norms and actual usage of GT.*

*Hypothesis 8: Social acceptability mediates the relationship between subjective norms and behavioural intentions towards GT.*

### *Structural model*

The model below was developed from the preceding literature review (see Figure 1). It clearly depicts the study's hypotheses.

## **Methodology**

## ***Sample and respondent characteristics***

After receiving institutional ethics approval, an online cross-sectional survey was conducted with 833 participants via the Centiment market research platform. Participants were compensated in accordance with platform policies. A convenience sampling method was used because not all potential respondents were reachable via established panels such as Centiment. Internet marketing panels are popular in survey research for their cost-effectiveness and ability to quickly gather large, diverse samples, thereby reducing data collection time. Their standardized procedures also promote consistency and facilitate replication of studies (Boas et al., 2020). Participants were briefed on GT before filling out the questionnaire.

### *Measurement and questionnaire development*

Participants indicated their level of agreement with several statements using a 5-point Likert scale (1 = completely disagree, 5 = completely agree). Research has explored the suitability of 5-, 7-, and 10-point Likert scales for parametric analyses, with 5- and 7-point options being most frequently used in social science. Findings show that these scale types produce largely similar results in statistical analyses (Huh & Gim, 2025). The constructs, measurement scales and their sources are presented in Supplementary File A.

### *Method of statistical analysis*

Partial least squares structural equation modelling (PLS-SEM) was employed due to its strong predictive orientation and its ability to identify key drivers of endogenous constructs, rather than focusing solely on theory confirmation. Unlike covariance-based SEM (CB-SEM), which aims to reproduce covariance matrices and assess overall model fit, PLS-SEM emphasizes maximizing explained variance ( $R^2$ ) and predictive accuracy, including out-of-sample prediction (Hair et al., 2022; Shmueli et al., 2019). This predictive focus makes PLS-SEM particularly suitable for research in emerging or evolving domains, such as GT adoption, where theoretical development is still ongoing (Chin, 1998; Henseler et al., 2016).

Furthermore, PLS-SEM is less restrictive regarding assumptions about data distribution and performs well with non-normal data and complex models involving multiple constructs and indicators (Hair et al., 2022; Ringle et al., 2020).

The characteristics of the data further support the use of PLS-SEM. CB-SEM typically requires relatively large sample sizes and assumes multivariate normality to ensure stable parameter estimates and reliable model fit indices (Kline, 2015; West et al., 1995). These assumptions are often difficult to satisfy in applied and managerial research contexts. In contrast, PLS-SEM is more flexible, performing well with smaller samples, non-normal data, and complex model structures involving multiple constructs and indicators (J. Hair et al., 2024b; JHair et al., 2011b; Lowry & Gaskin, 2014). Moreover, PLS-SEM facilitates the assessment of predictive validity through procedures such as Stone–Geisser’s  $Q^2$  and  $PLS_{predict}$ , enabling researchers to evaluate out-of-sample predictive performance (Hair et al., 2020; Shmueli et al., 2019). This predictive capability provides insights beyond those typically offered by CB-SEM. Given the study’s objective of understanding how knowledge is transformed and applied in dynamic, interconnected contexts such as GT, PLS-SEM is an appropriate and robust methodological choice.

## Data analysis

### Background data

Sample characteristics for this study ( $N = 833$ ) are available in Supplementary File B. The mean age of respondents was 47.6 years ( $SD = 17.3$ ). Correlation matrices for the endogenous and exogenous indicator variables are reported separately in Supplementary File C.

### Preparation and checking of data

In the preliminary stage, data quality and suitability were systematically assessed. This included evaluating sample size adequacy, detecting potential outliers, examining data distribution, and verifying measurement levels and scale coding (Richter et al., 2020). Sample adequacy was first determined using Cochran’s formula for continuous data (Cochran, 1977). Based on a significance level of 0.025 in each tail ( $z = 1.96$ ), a standard deviation of 0.8 on a 5-point scale, and a margin of error of 0.15, the minimum required sample size was 137. Given that required sample sizes stabilize at larger population levels (Qualtrics, 2025), the final sample of 833 respondents is considered adequate and representative.

Additional considerations for PLS-SEM further support this conclusion. Prior research indicates that a minimum sample of approximately 155 observations is sufficient to detect path coefficients in the range of 0.11–0.20 at a 0.05 significance level (Hair et al., 2022). Similarly, the inverse-square-root method suggests a minimum of 154 observations under comparable conditions (Hair et al., 2022; Kock & Hadaya, 2018). Accordingly, the sample size of 833 substantially exceeds these requirements.

Outliers were identified using Mahalanobis distance, a widely recommended approach for detecting multivariate anomalies (Grande, 2016; Hair et al., 2010). This process resulted in the removal of 25 observations, enhancing data robustness. After removing the outliers, the final sample size was 808. All constructs were measured using metric or quasi-metric Likert-type scales to ensure consistency with analytical requirements.

Although PLS-SEM does not require strict distributional assumptions (Richter et al., 2020), distributional properties were examined to ensure robustness. Skewness and kurtosis were assessed using SPSS version 26 (see Supplementary File D). Following established guidelines, values within  $\pm 2$  of the mean indicate acceptable normality (Hair et al., 2022). All variables met this criterion, suggesting no need for corrective action.

Normality was further assessed using the Kolmogorov–Smirnov and Shapiro–Wilk tests. While both tests were statistically significant, indicating deviations from perfect normality, such results are common in large samples due to test sensitivity. Given that skewness and kurtosis remained within acceptable ranges, any impact on statistical power is considered minimal, and the data are deemed suitable for subsequent analysis (see Supplementary File D).

## Common method bias

To assess potential common method bias (CMB), this study applied the full collinearity test, a variance-based SEM technique recommended as an alternative to traditional methods (Lindell & Whitney, 2001). This approach is particularly suitable for PLS-SEM, as it allows simultaneous evaluation of vertical and lateral collinearity, following the procedure proposed by Kock and Lynn (2012). A random dummy variable with values ranging from 0 to 1 was incorporated into the structural model, and all latent constructs were regressed on this variable. The PLS-SEM analysis was then conducted, and variance inflation factors (VIFs) were examined. All VIF values fell below the conservative threshold of 3.3 (Hair et al., 2018), suggesting that collinearity is not a concern and that common method bias is unlikely to affect the results.

## Assessment of the measurement model

The measurement model assessment began with an evaluation of indicator reliability. A bias-corrected and accelerated bootstrapping procedure was used to test the significance of indicator loadings. All loadings exceeded the recommended threshold of 0.70 (see Supplementary File E), indicating strong and significant relationships between the indicators and their respective constructs (Rosenbusch et al., 2018). Thus, there was no need to remove any indicators from the variable set (Hair et al., 2022).

Internal consistency reliability was also assessed (see Supplementary File E). Cronbach's alpha, which provides a conservative estimate, and composite reliability, which may overestimate reliability (recommended range: 0.70–0.95), were both examined. Accordingly, true reliability is expected to lie

between these two measures. Convergent validity was evaluated using the average variance extracted (AVE), with all values exceeding the recommended threshold of 0.50, indicating adequate construct validity.

Discriminant validity was subsequently assessed using the Heterotrait–Monotrait (HTMT) ratio (Hair et al., 2022). There were issues with discriminant validity between the constructs of social acceptability and subjective norms. To decrease the average heteromethod-heterotrait correlations, the literature advises eliminating items that are strongly correlated with items in the opposing construct (Hair et al., 2022); thus, variables NORM3 and SOCACC1 were removed. After this, the bootstrapping-based HTMT confidence intervals were all significant, indicating acceptable discriminant validity.

## Assessment of the structural model

The evaluation of the structural model began with an assessment of collinearity among the exogenous constructs using variance inflation factors (VIF). All VIF values were below the recommended strict threshold of 3.3, indicating no collinearity concerns (Hair et al., 2011). Next, predictive validity was assessed using  $R^2$  and Stone–Geisser’s  $Q^2$ . According to established guidelines,  $R^2$  values of 0.75, 0.50, and 0.25 represent substantial, moderate, and weak explanatory power, respectively. In this study, the  $R^2$  and adjusted  $R^2$  values for actual GT usage were 0.422 and 0.421, indicating moderate explanatory power.

Predictive relevance was further evaluated using  $Q^2$ . The obtained  $Q^2$  value of 0.195 suggests low-to-moderate predictive relevance (Hair et al., 2020). Overall, the model demonstrates moderate predictive capability. This level of predictive power is reasonable, given that actual usage was modelled with only one predictor, behavioural intentions. The literature indicates that as additional predictors are introduced,  $R^2$  increases because the model captures a greater share of the explained variance (Hair et al., 2019, 2022).

Finally, statistical power was assessed to address potential concerns related to data distribution. With 11 predictors, an  $R^2$  of 0.422, a significance level of 0.05, and a sample size of 808, the estimated statistical power was 1.0, well above the recommended threshold of 0.80, confirming the robustness of the analysis (Richter et al., 2020; Soper, 2025).

## Hypotheses testing

The final stage of structural model evaluation involves assessing the significance of the path coefficients, corresponding to hypothesis testing (see Table 1). However, relying solely on statistical significance is insufficient; effect sizes should also be considered (Cohen, 1992; Klein, 2005). This is particularly important because large samples may yield statistically significant results that are not practically meaningful. Consequently, p-values and bootstrapped confidence intervals alone do not provide a complete interpretation of the results (Sullivan & Feinn, 2012).

Effect sizes offer a more meaningful assessment of the magnitude of relationships, with values of 0.02, 0.15, and 0.35 indicating small, medium, and large effects, respectively (Hair et al., 2022). Importantly, because effect sizes are not influenced by sample size, they facilitate more meaningful comparisons across studies (Hair et al., 2010).

Table 1  
The significance of the path coefficients in the model

(Source: Authors' own work).

| # | Hypothesis                                                                      | Path coefficient | 5% bootstrapping confidence interval |       | Hypotheses support | Effect size ( $f^2$ ) | Effect size description |
|---|---------------------------------------------------------------------------------|------------------|--------------------------------------|-------|--------------------|-----------------------|-------------------------|
|   |                                                                                 |                  | 2.5%                                 | 97.5% |                    |                       |                         |
| 1 | Subjective norms → Social acceptability                                         | 0.725            | 0.683                                | 0.761 | Yes                | 1.107                 | Large                   |
| 2 | Social acceptability → Behavioural intentions                                   | 0.281            | 0.192                                | 0.369 | Yes                | 0.058                 | Small to medium         |
| 3 | Subjective norms → Behavioural intentions                                       | 0.360            | 0.267                                | 0.442 | Yes                | 0.096                 | Medium to small         |
| 4 | Behavioural intentions → Actual usage                                           | 0.649            | 0.606                                | 0.689 | Yes                | 0.729                 | Large                   |
| 5 | Social acceptability → Behavioural intentions → Actual usage                    | 0.183            | 0.124                                | 0.243 | Yes                | .                     | .                       |
| 6 | Subjective norms → Social acceptability → Behavioural intentions → Actual usage | 0.132            | 0.090                                | 0.177 | Yes                | .                     | .                       |
| 7 | Subjective norms → Behavioural intentions → Actual usage                        | 0.234            | 0.174                                | 0.291 | Yes                | .                     | -                       |
| 8 | Subjective norms → Social acceptability → Behavioural intentions                | 0.204            | 0.139                                | 0.268 | Yes                | .                     | -                       |

The results presented in Table 1 indicate strong empirical support for all hypothesized relationships in the model. Subjective norms exert a substantial positive effect on social acceptability ( $\beta = 0.725$ ), indicating a large effect size, and also significantly influence behavioural intentions ( $\beta = 0.360$ ), indicating a moderate effect. Social acceptability, in turn, positively affects behavioural intentions ( $\beta = 0.281$ ), although with a smaller effect size, suggesting a complementary rather than dominant role. Behavioural intentions demonstrate a strong positive impact on actual usage ( $\beta = 0.649$ ), highlighting their central role in translating perceptions into behaviour. Importantly, all indirect effects are significant, confirming the presence of multiple mediation pathways. Specifically, behavioural intentions mediate the relationship between social acceptability and actual usage, while both social acceptability and behavioural intentions jointly mediate the effect of subjective norms on actual usage. Additionally, social acceptability partially mediates the relationship between subjective norms and behavioural intentions. The findings underscore a robust, hierarchical influence structure, in which social norms shape behaviour both directly and indirectly, through social acceptability and behavioural intentions.

## Discussion

This study examined the behavioural mechanisms underlying GT uptake by integrating subjective norms, social acceptability, behavioural intentions, and actual use into a single explanatory framework. Overall, the findings provide strong empirical support for the proposed model and demonstrate that social influence affects GT uptake through both direct and indirect pathways. In particular, subjective norms strongly influenced perceptions of social acceptability and behavioural intentions, while behavioural intentions emerged as the strongest predictor of actual GT use. The significant sequential mediation effects further indicate that social influence is translated into behaviour through multiple interconnected mechanisms rather than through a single direct pathway.

The strong relationship between subjective norms and behavioural intentions is consistent with the Theory of Planned Behaviour (Ajzen, 1991; Fishbein & Ajzen, 2011) and previous studies of healthcare technology adoption (Holden & Karsh, 2010; Rahimi et al., 2018). Healthcare decisions are frequently shaped by recommendations from healthcare professionals, family members, and broader social networks, particularly when technologies involve uncertainty, ethical considerations, or potentially life-changing consequences (Henneman et al., 2013; Oliveri et al., 2016). The present findings reinforce the importance of these normative influences and suggest that decisions regarding GT are socially embedded rather than purely individual or rational evaluations.

Beyond confirming existing behavioural models, this study demonstrates that social acceptability represents an important intermediary mechanism linking subjective norms with behavioural intentions. Whereas subjective norms reflect perceived expectations from significant others, social acceptability captures broader perceptions that a healthcare intervention is legitimate, ethically appropriate, and supported within society (Gordon et al., 2022; Wutz et al., 2023). The significant pathway from subjective norms to social acceptability suggests that social endorsement contributes to wider perceptions of legitimacy, which subsequently strengthen intentions to undergo GT. This finding extends previous

applications of the TPB by showing that social influence operates not only through interpersonal normative pressure but also through broader evaluations of societal appropriateness, particularly in ethically sensitive healthcare contexts (Hassan et al., 2024).

Behavioural intentions remained the strongest predictor of actual GT use, supporting extensive evidence demonstrating that intentions constitute the most proximal determinant of health behaviour (Ajzen, 1991; Holden & Karsh, 2010; Zhang et al., 2025). However, the observed indirect effects demonstrate that favourable intentions develop through multiple preceding behavioural processes. Rather than acting independently, subjective norms and social acceptability jointly contribute to the formation of behavioural intentions, thereby helping to explain how individuals progress from social influence to actual healthcare utilization. These findings also contribute to the literature addressing the intention–behaviour gap by demonstrating that intermediate behavioural mechanisms are required to translate favourable perceptions into actual action (Ruyobeza et al., 2025; Sheeran & Webb, 2016).

From a health services perspective, the findings have broader implications for the implementation of precision medicine. Successful implementation depends not only on expanding access to genetic testing but also on creating conditions that encourage patients to engage with available services. Implementation research increasingly recognizes that successful adoption of healthcare innovations requires attention to behavioural, organizational, and contextual factors in addition to clinical effectiveness (Damschroder et al., 2022; Nilsen, 2015). The present findings suggest that perceptions of social legitimacy and public acceptability constitute important behavioural determinants that may influence whether patients ultimately utilize precision medicine services. Consequently, implementation strategies should extend beyond improving service availability and simultaneously address public understanding, ethical concerns, and community acceptance of genetic testing.

The findings also contribute to implementation science by identifying a behavioural mechanism through which social contexts influence healthcare utilization. While implementation frameworks frequently emphasize organizational readiness, contextual influences, and implementation processes (Damschroder et al., 2022), comparatively less attention has been devoted to understanding how broader societal acceptance shapes patient engagement with healthcare innovations. By demonstrating that social acceptability mediates the relationship between subjective norms and actual GT use, this study suggests that successful implementation of precision medicine depends not only on healthcare system capacity but also on fostering public confidence, social legitimacy, and ethical acceptance of emerging genomic technologies.

Overall, this study advances current understanding of healthcare technology uptake by integrating social and behavioural mechanisms within a single explanatory framework. Existing behavioural models have traditionally emphasized individual cognitive evaluations such as attitudes, perceived usefulness, or behavioural intentions (Davis, 1989; Rogers, 2003; Venkatesh et al., 2003). The present findings demonstrate that broader social processes also play an important role in determining healthcare utilization. By identifying social acceptability as a distinct intermediary construct, the study provides a

more comprehensive explanation of how social influence contributes to patient uptake of genetic testing and offers a behavioural perspective that may be applicable to other emerging healthcare technologies.

## Implications

### Implications for health services research

This study makes several contributions to health services research by advancing understanding of the behavioural mechanisms that influence patient uptake of genetic testing (GT). While previous research has largely emphasized individual cognitive determinants of healthcare technology adoption, such as perceived usefulness, attitudes, and behavioural intentions (Ajzen, 1991; Holden & Karsh, 2010; Rahimi et al., 2018), the present study demonstrates that social influence operates through a more complex process involving both social acceptability and behavioural intentions. By integrating these constructs within a single explanatory framework, the study provides a more comprehensive explanation of how social contexts shape patient engagement with precision medicine services.

First, the findings extend the Theory of Planned Behaviour by identifying social acceptability as a distinct intermediary mechanism linking subjective norms to behavioural intentions (Ajzen, 1991; Fishbein & Ajzen, 2011). Whereas subjective norms capture perceived social expectations, social acceptability reflects broader perceptions that genetic testing is socially legitimate, ethically appropriate, and supported within society (Gordon et al., 2022; Wutz et al., 2023). Distinguishing these constructs provides a more nuanced understanding of how social influence affects healthcare decision-making, particularly for interventions involving ethical, privacy, and trust-related considerations.

Second, the study contributes to the growing literature examining the intention–behaviour relationship in healthcare. Although behavioural intentions remained the strongest predictor of actual GT uptake, the significant indirect effects demonstrate that favourable intentions develop through multiple interconnected behavioural processes rather than emerging solely from individual cognitive evaluations. These findings support previous research highlighting the complexity of the intention–behaviour gap and suggest that intermediary behavioural mechanisms should be incorporated into future models of healthcare utilization (Ruyobeza et al., 2025; Sheeran & Webb, 2016).

Third, the findings contribute to research on the implementation of precision medicine by demonstrating that successful implementation depends not only on the clinical effectiveness and availability of genomic services but also on behavioural and social determinants that influence patient engagement. Implementation science increasingly recognizes that successful integration of healthcare innovations requires attention to behavioural, organizational, and contextual factors alongside evidence of clinical benefit (Damschroder et al., 2022; Nilsen, 2015). The present findings complement these perspectives by showing that perceptions of social legitimacy and acceptability represent important behavioural mechanisms through which patients engage with emerging genomic services.

Finally, the proposed framework provides a foundation for future research examining patient uptake of other precision medicine initiatives and emerging healthcare innovations. As healthcare systems continue to integrate genomic medicine, artificial intelligence, digital health technologies, and personalized care into routine practice (Johnson et al., 2021), understanding how social influence shapes patient engagement will become increasingly important. Future research should therefore investigate how behavioural, organizational, and health system factors interact to influence the successful implementation and sustained uptake of innovative healthcare services.

## Implications for healthcare practice

The findings have important implications for healthcare providers, health system managers, policymakers, and organizations responsible for implementing precision medicine initiatives. As genetic testing becomes increasingly integrated into routine healthcare, successful implementation will depend not only on expanding service availability but also on understanding the behavioural and social factors that influence patient uptake. The present findings suggest that implementation strategies should address the broader social context in which individuals make decisions about genetic testing, thereby promoting patient engagement, equitable access, and successful integration of genomic services into healthcare delivery.

First, the strong influence of subjective norms indicates that implementation efforts should leverage trusted social and professional networks to encourage genetic testing uptake. Healthcare professionals, patient advocates, community leaders, and individuals with lived experience can serve as credible sources of information that reinforce positive social expectations and normalize participation in genetic testing. Communication strategies that incorporate trusted voices and community endorsement may therefore be more effective than information campaigns that rely solely on the provision of factual information.

Second, the findings demonstrate that social acceptability plays a pivotal role in translating social influence into behavioural intentions. Consequently, implementation initiatives should extend beyond raising awareness of genetic testing and actively address concerns related to ethics, privacy, discrimination, and data governance. Transparent communication regarding informed consent, data security, regulatory oversight, and the clinical value of genetic testing may strengthen public trust and enhance perceptions that these services are both socially legitimate and appropriate. Such efforts are particularly important for technologies that involve sensitive personal information and may evoke ethical or societal concerns.

Third, behavioural intentions emerged as the strongest predictor of actual genetic testing uptake, highlighting the importance of supporting individuals once they have decided to pursue testing. Healthcare organizations can facilitate this transition by reducing practical barriers throughout the patient journey. Integrating genetic testing into routine clinical pathways, simplifying referral and appointment processes, improving service accessibility, and providing patient decision aids and follow-

up support may help individuals translate positive intentions into completed testing. These findings suggest that implementation strategies should address both behavioural and structural barriers to maximize uptake.

Finally, the significant indirect effects observed in the model indicate that implementation efforts should adopt a comprehensive, multi-level approach rather than focusing on individual determinants in isolation. Interventions that simultaneously strengthen positive social norms, increase perceptions of social acceptability, and reduce practical barriers are likely to be more effective than initiatives targeting only a single aspect of patient decision-making. Coordinated implementation strategies that combine public engagement, clinician communication, organizational support, and accessible service delivery may therefore achieve greater and more sustainable improvements in genetic testing uptake.

Although this study focuses on genetic testing, the findings have broader implications for the implementation of precision medicine and other emerging healthcare innovations. As healthcare systems increasingly integrate genomic medicine, artificial intelligence, digital health technologies, and personalized care into routine practice, implementation success will depend not only on technological capability and clinical effectiveness but also on public trust, perceived social legitimacy, and patient acceptance. Addressing these behavioural determinants alongside improvements in healthcare delivery may facilitate the successful implementation and sustained uptake of innovative healthcare services.

## Limitations and Future Research

This study should be interpreted in light of several limitations. First, the cross-sectional research design limits causal inference. Although the proposed relationships are theoretically grounded and supported by the empirical findings, longitudinal studies are needed to examine how perceptions of social influence, social acceptability, and behavioural intentions evolve over time and influence subsequent genetic testing uptake.

Second, the study relied on self-reported measures collected through an online survey, which may be subject to response biases such as social desirability and recall bias. Although established measurement scales and statistical procedures were used to minimize common method bias, future studies could strengthen the evidence by incorporating objective measures of genetic testing utilization or healthcare records where appropriate.

Third, the sample was drawn from residents of British Columbia, Canada. Although this provides valuable insight into a publicly funded healthcare system with increasing availability of genomic services, healthcare systems, cultural norms, and implementation strategies vary across jurisdictions. Replication in other provinces and countries would help establish the generalizability of the findings.

Fourth, the study examined behavioural determinants at the individual level and did not explicitly consider organizational or system-level implementation factors, such as provider readiness, organizational capacity, reimbursement policies, or service availability. Future research could integrate

patient-level behavioural models with implementation science frameworks to examine how individual, organizational, and health system factors jointly influence the successful implementation and uptake of genetic testing services.

Finally, this study focused on genetic testing as an empirical context. Although the proposed framework may be applicable to other precision medicine initiatives and emerging healthcare technologies, additional research is needed to determine whether the relationships observed here extend to other genomic applications, digital health interventions, and personalized healthcare services. Comparative studies across different healthcare settings and patient populations would further advance understanding of the behavioural mechanisms that support successful implementation of healthcare innovations.

## Conclusions

This study examined the behavioural mechanisms underlying genetic testing uptake by integrating subjective norms, social acceptability, behavioural intentions, and actual use within a single explanatory framework. The findings demonstrate that social influence affects genetic testing uptake through both direct and indirect pathways, with behavioural intentions serving as the strongest predictor of actual use. In particular, the results identify social acceptability as an important intermediary construct through which subjective norms shape behavioural intentions, providing a more comprehensive understanding of how social influences translate into healthcare utilization.

These findings contribute to health services research by extending current understanding of patient uptake of precision medicine services. While previous studies have primarily emphasized individual cognitive determinants of healthcare technology adoption, the present study demonstrates that broader social processes also influence engagement with genetic testing. By identifying social acceptability as a key behavioural mechanism, the study offers new insights into how implementation of precision medicine may be supported through interventions that strengthen public trust, social legitimacy, and community acceptance alongside improvements in healthcare delivery.

From a practical perspective, the findings suggest that successful implementation of genetic testing requires more than expanding service availability. Healthcare organizations and policymakers should consider implementation strategies that simultaneously address social norms, ethical and privacy concerns, patient education, and structural barriers to access. Such comprehensive approaches may strengthen patient engagement, promote equitable uptake of genetic testing, and facilitate the integration of genomic medicine into routine healthcare practice.

Although this study focused on genetic testing, the proposed framework may also be relevant to other precision medicine initiatives and emerging healthcare innovations. Future research should examine whether the relationships identified in this study generalize across different healthcare settings, patient populations, and genomic applications, as well as investigate additional contextual factors that may

influence implementation and sustained uptake. Such work will further advance understanding of the behavioural processes that support successful implementation of innovative healthcare services.

## Declarations

**Funding:** GenomeBC has funded this research project.

**Data availability:** No. The datasets generated and/or analyzed in the current study are not publicly available because the authors do not own the data.

**AI-generated content disclosure statement:** The author abides by Emerald's principles for the use of generative AI and has reviewed the terms and conditions or terms of use associated with the AI tool used to ensure compliance. During the preparation of this work, the author used ChatGPT v5.5 to copyedit (correcting, editing, formatting, modifying, or refining). After using this tool, the author must take full responsibility for the accuracy of all content considered for publication and verify that the material submitted, including citations and references, is correct, appropriately correlates with the research, and aligns with Emerald's research and publishing ethics.

**Ethical approval:** This confirms that this research study has adhered to all applicable ethical standards and guidelines throughout the research process. This research was approved by the Thompson Rivers University Ethics Board on [Ethics Approval Number: 104732], and it was conducted following the ethical guidelines set forth by the Tri-Council Policy Statement: Ethical Conduct for Research Involving Humans (TCPS 2).

**Informed consent:** Prior to commencing data collection, the participants were provided with detailed information about the study's procedures and fully informed about the purpose of the research and the study's aims, their rights as respondents (including the right to refuse participation or withdraw from the study at any time), and the measures taken to ensure their confidentiality and anonymity. Informed consent was obtained from all participants before taking part in the study. Furthermore, the authors confirm that the study adheres to the relevant ethical guidelines for human participants, and that it followed ethical measures in compliance with institutional and international guidelines, including: Maintaining and respecting the autonomy, confidentiality, and anonymity of all respondents throughout the study via paper surveys at the University, using collected data solely for the purposes outlined in the study, ensuring transparency in data handling and reporting and avoiding any form of coercion or undue influence in securing participation.

**AI-generated content disclosure statement:** The author abides to the principles for the use of generative AI and has reviewed the terms and conditions or terms of use associated with the AI tool used to ensure compliance. During the preparation of this work, the author used ChatGPT v5.5 to copyedit (correcting, editing, formatting, modifying, or refining). After using this tool, the author must take full responsibility for the accuracy of all content considered for publication and verify that the material submitted,

including citations and references, is correct, appropriately correlates with the research, and aligns with Emerald's research and publishing ethics.

**Ethical approval:** This confirms that this research study has adhered to all applicable ethical standards and guidelines throughout the research process. This research was approved by the Thompson Rivers University Ethics Board on [Ethics Approval Number: 104732], and it was conducted following the ethical guidelines set forth by the Tri-Council Policy Statement: Ethical Conduct for Research Involving Humans (TCPS 2).

**Informed consent:** Prior to commencing data collection, the participants were provided with detailed information about the study's procedures and fully informed about the purpose of the research and the study's aims, their rights as respondents (including the right to refuse participation or withdraw from the study at any time), and the measures taken to ensure their confidentiality and anonymity. Informed consent was obtained from all participants before taking part in the study. Furthermore, the authors confirm that the study adheres to the relevant ethical guidelines for human participants, and that it followed ethical measures in compliance with institutional and international guidelines, including: Maintaining and respecting the autonomy, confidentiality, and anonymity of all respondents throughout the study via paper surveys at the University, using collected data solely for the purposes outlined in the study, ensuring transparency in data handling and reporting and avoiding any form of coercion or undue influence in securing participation.

## References

1. Ajzen, I. The theory of planned behavior. *Organ. Behav. Hum Decis. Process.* **50** (2), 179–211. [https://doi.org/10.1016/0749-5978\(91\)90020-T](https://doi.org/10.1016/0749-5978(91)90020-T) (1991).
2. Ajzen, I. The theory of planned behaviour: Reactions and reflections. *Psychol. Health.* **26** (9), 1113–1127. <https://doi.org/10.1080/08870446.2011.613995> (2011).
3. Alelyani, T. Decoding trust in large language models for healthcare in Saudi Arabia. *Sci. Rep.* **15** (1), 35276. <https://doi.org/10.1038/s41598-025-18404-0> (2025).
4. Baron, R. M. & Kenny, D. A. The moderator–mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *J. Personal. Soc. Psychol.* **51** (6), 1173–1182. <https://doi.org/10.1037/0022-3514.51.6.1173> (1986).
5. Boas, T. C., Christenson, D. P. & Glick, D. M. Recruiting large online samples in the United States and India: Facebook, Mechanical Turk, and Qualtrics. *Political Sci. Res. Methods.* **8** (2), 232–250. <https://doi.org/10.1017/psrm.2018.28> (2020).
6. Chin, W. W. Commentary: Issues and opinion on Structural Equation Modelling. *MIS Q.* **22** (1), vii–xvi (1998).
7. Cochran, W. G. *Sampling Techniques* (Wiley, 1977).
8. Cohen, J. Things I Have Learned (so far). In *Methodological Issues and Strategies in Clinical Research* (Vol. 45, 1304–1312). American Psychological Association.

- <https://doi.org/10.1037/10109-028> (1992).
9. Damschroder, L. J., Reardon, C. M., Widerquist, M. A. O. & Lowery, J. The updated consolidated framework for implementation research based on user feedback. *Implement. Sci.* **17** (1), 75. <https://doi.org/10.1186/s13012-022-01245-0> (2022).
  10. Davis, F. D. Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Q.* **13** (3), 319–340. <https://doi.org/10.2307/249008> (1989a).
  11. Davis, F. D. *Technology acceptance model: TAM* (University of Michigan, 1989b).
  12. Dhagarra, D., Goswami, M. & Kumar, G. Impact of trust and privacy concerns on technology acceptance in healthcare: an Indian perspective. *Int. J. Med. Informatics.* **141**, 104164. <https://doi.org/10.1016/j.ijmedinf.2020.104164> (2020).
  13. Fishbein, M. & Ajzen, I. *Predicting and Changing Behavior* (Psychology, 2011). <https://doi.org/10.4324/9780203838020>
  14. Gao, Y., Li, H. & Luo, Y. An empirical study of wearable technology acceptance in healthcare. *Industrial Manage. Data Syst.* **115** (9), 1704–1723. <https://doi.org/10.1108/IMDS-03-2015-0087> (2015).
  15. Gordon, J. A., Balta-Ozkan, N. & Nabavi, S. A. Beyond the triangle of renewable energy acceptance: The five dimensions of domestic hydrogen acceptance. *Appl. Energy.* **324**, 119715. <https://doi.org/10.1016/j.apenergy.2022.119715> (2022).
  16. Grande, T. *Identifying Multivariate Outliers with Mahalanobis Distance in SPSS*. (2016). <https://www.youtube.com/watch?v=AXLAX6r5JgE>
  17. Hair, J. F., Black, W. C., Babin, B. J. & Anderson, R. E. Multivariate Data Analysis. In *Vectors*. Pearson. (2010).
  18. Hair, J. F., Howard, M. C. & Nitzl, C. Assessing measurement model quality in PLS-SEM using confirmatory composite analysis. *J. Bus. Res.* **109**, 101–110. <https://doi.org/10.1016/j.jbusres.2019.11.069> (2020).
  19. Hair, J. F., Hult, G. T., Ringle, C. & Sarstedt, M. A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM). In Sage (2nd ed.). Sage. (2022).
  20. Hair, J. F., Ringle, C. M. & Sarstedt, M. PLS-SEM: Indeed a Silver Bullet. *J. Mark. Theory Pract.* **19** (2), 139–152. <https://doi.org/10.2753/MTP1069-6679190202> (2011).
  21. Hair, J. F., Risher, J. J., Sarstedt, M. & Ringle, C. M. When to use and how to report the results of PLS-SEM. *Eur. Bus. Rev.* **31** (1), 2–24. <https://doi.org/10.1108/EBR-11-2018-0203> (2019).
  22. Hair, J., Sarstedt, M., Ringle, C. & Gudergan, S. *Advanced Issues in Partial Least Squares Structural Equation Modeling* (Sage, 2024).
  23. Hassan, M., Kushniruk, A. & Borycki, E. Barriers to and facilitators of artificial intelligence adoption in health care: scoping review. *JMIR Hum. Factors.* **11**, e48633. <https://doi.org/10.2196/48633> (2024).
  24. Henneman, L. et al. Public attitudes towards genetic testing revisited: comparing opinions between 2002 and 2010. *Eur. J. Hum. Genet.* **21** (8), 793–799. <https://doi.org/10.1038/ejhg.2012.271> (2013).

25. Henseler, J., Hubona, G. & Ray, P. A. Using PLS path modeling in new technology research: updated guidelines. *Industrial Manage. Data Syst.* **116** (1), 2–20. <https://doi.org/10.1108/IMDS-09-2015-0382> (2016).
26. Ho, J. C. & Lin, C. Y. Acceptance of preventive genetic testing: the roles of innovation attributes, consumer characteristics, and contextual factors. *Int. J. Pharm. Healthc. Mark.* 1–21. <https://doi.org/10.1108/IJPHM-07-2025-0154> (2025a).
27. Ho, J. C. & Lin, C. Y. Acceptance of preventive genetic testing: the roles of innovation attributes, consumer characteristics, and contextual factors. *Int. J. Pharm. Healthc. Mark.* 1–21. <https://doi.org/10.1108/IJPHM-07-2025-0154> (2025b).
28. Holden, R. J. & Karsh, B. T. The technology acceptance model: its past and its future in health care. *J. Biomed. Inform.* **43** (1), 159–172. <https://doi.org/10.1016/j.jbi.2009.07.002> (2010).
29. Huh, I. & Gim, J. Exploration of Likert scale in terms of continuous variable with parametric statistical methods. *BMC Med. Res. Methodol.* **25** (1), 218. <https://doi.org/10.1186/s12874-025-02668-1> (2025).
30. Hung, M. C. & Jen, W. Y. The adoption of mobile health management services: an empirical study. *J. Med. Syst.* **36** (3), 1381–1388. <https://doi.org/10.1007/s10916-010-9600-2> (2012).
31. Johnson, K. B. et al. Precision medicine, AI, and the future of personalized health care. *Clin. Transl. Sci.* **14** (1), 86–93. <https://doi.org/10.1111/cts.12884> (2021a).
32. Johnson, K. B. et al. Precision medicine, AI, and the future of personalized health care. *Clin. Transl. Sci.* **14** (1), 86–93. <https://doi.org/10.1111/cts.12884> (2021b).
33. Klein, D. F. Beyond significance testing: Reforming data analysis methods in behavioural research. *Am. J. Psychiatry.* **162** (3), 643–644. <https://doi.org/10.1176/appi.ajp.162.3.643-a> (2005).
34. Kline, P. *A Handbook of Test Construction (Psychology Revivals)* (Routledge, 2015). <https://doi.org/10.4324/9781315695990>
35. Kock, N. & Hadaya, P. Minimum sample size estimation in PLS-SEM: The inverse square root and gamma-exponential methods. *Inform. Syst. J.* **28** (1), 227–261. <https://doi.org/10.1111/isj.12131> (2018).
36. Kock, N. & Lynn, G. S. Lateral collinearity and misleading results in variance-based SEM: An illustration and recommendations. *Journal Association Inform. Systems*, **13**(7). (2012).
37. Lee, A. T., Ramasamy, R. K. & Subbarao, A. Understanding psychosocial barriers to healthcare technology adoption: a review of TAM technology acceptance model and unified theory of acceptance and use of technology and UTAUT frameworks. *Healthcare* **13** (3), 250. <https://doi.org/10.3390/healthcare13030250> (2025).
38. Lee, J. W. Diffusion of innovations. In *Encyclopedia of Sport Management* (pp. 266–268). Edward Elgar Publishing. (2024). <https://doi.org/10.4337/9781035317189.ch157>
39. Lindell, M. K. & Whitney, D. J. Accounting for common method variance in cross-sectional research designs. *J. Appl. Psychol.* **86** (1), 114–121. <https://doi.org/10.1037/0021-9010.86.1.114> (2001).

40. Lowry, P. B. & Gaskin, J. Partial Least Squares (PLS) Structural Equation Modeling (SEM) for Building and Testing Behavioral Causal Theory: When to Choose It and How to Use It. *IEEE Trans. Prof. Commun.* **57** (2), 123–146. <https://doi.org/10.1109/TPC.2014.2312452> (2014).
41. Nilsen, P. Making sense of implementation theories, models and frameworks. *Implement. Sci.* **10** (1), 53. <https://doi.org/10.1186/s13012-015-0242-0> (2015).
42. Oliveri, S. et al. Health orientation, knowledge, and attitudes toward genetic testing and personalized genomic services: Preliminary data from an Italian sample. *BioMed Research International*, 2016, 1–9. (2016). <https://doi.org/10.1155/2016/6824581>
43. Preacher, K. J. & Hayes, A. F. Asymptotic and resampling strategies for assessing and comparing indirect effects in multiple mediator models. *Behav. Res. Methods.* **40** (3), 879–891. <https://doi.org/10.3758/BRM.40.3.879> (2008).
44. Qualtrics. *Sample Size Calculator*. (2025). <https://www.qualtrics.com/blog/calculating-sample-size/>
45. Rahimi, B., Nadri, H., Afshar, L., Timpka, T. & H., & A systematic review of the technology acceptance model in health informatics. *Appl. Clin. Inf.* **9** (3), 604–634. <https://doi.org/10.1055/s-0038-1668091> (2018).
46. Richter, N. F., Schubring, S., Hauff, S., Ringle, C. M. & Sarstedt, M. When predictors of outcomes are necessary: guidelines for the combined use of PLS-SEM and NCA. *Industrial Manage. Data Syst.* **120** (12), 2243–2267. <https://doi.org/10.1108/IMDS-11-2019-0638> (2020).
47. Ringle, C. M., Sarstedt, M., Mitchell, R. & Gudergan, S. P. Partial least squares structural equation modeling in HRM research. *Int. J. Hum. Resource Manage.* **31** (12), 1617–1643. <https://doi.org/10.1080/09585192.2017.1416655> (2020).
48. Rogers, E. M. *Diffusion of Innovations* (Free, 2003).
49. Rosenbusch, J., Ismail, I. R. & Ringle, C. M. The agony of choice for medical tourists: a patient satisfaction index model. *J. Hospitality Tourism Technol.* **9** (3), 267–279. <https://doi.org/10.1108/JHTT-10-2017-0107> (2018).
50. Ruyobeza, B., Grobbelaar, S. S., Saartjie & Botha, A. (eds) (Billy), & Forecasting the adoption of digital health technologies: The intention-expectation gap. *Evaluation and Program Planning*, 112, 102670. (2025). <https://doi.org/10.1016/j.evalprogplan.2025.102670>
51. Sheeran, P. & Webb, T. L. The Intention–Behavior Gap. *Soc. Pers. Psychol. Compass.* **10** (9), 503–518. <https://doi.org/10.1111/spc3.12265> (2016).
52. Shmueli, G. et al. Predictive model assessment in PLS-SEM: guidelines for using PLSpredict. *Eur. J. Mark.* **53** (11), 2322–2347 (2019a).
53. Shmueli, G. et al. Predictive model assessment in PLS-SEM: guidelines for using PLSpredict. *Eur. J. Mark.* **53** (11), 2322–2347 (2019b).
54. Soper, D. *Post-hoc Statistical Power Calculator for Multiple Regression*. (2025). <https://www.danielsoper.com/statcalc/calculator.aspx?id=9>

55. Sullivan, G. M. & Feinn, R. Using effect size—or why the p value is not enough. *J. Graduate Med. Educ.* **4** (3), 279–282. <https://doi.org/10.4300/jgme-d-12-00156.1> (2012).
56. Venkatesh, M., Davis & Davis, & User acceptance of information technology: Toward a unified view. *MIS Q.* **27** (3), 425. <https://doi.org/10.2307/30036540> (2003).
57. West, S. G., Finch, J. F. & Curran, P. J. Structural Equation Models with Non-normal Variables: Problems and Remedies. In (ed Hoyle, R. H.) *Structural Equation Modeling: Concepts, Issues, and Applications* (56–75). Sage. (1995).
58. Whetstone, M. & Goldsmith, R. Factors influencing intention to use personal health records. *Int. J. Pharm. Healthc. Mark.* **3** (1), 8–25. <https://doi.org/10.1108/17506120910948485> (2009).
59. Wu, J. H., Wang, S. C. & Lin, L. M. Mobile computing acceptance factors in the healthcare industry: A structural equation model. *Int. J. Med. Informatics.* **76** (1), 66–77. <https://doi.org/10.1016/j.ijmedinf.2006.06.006> (2007).
60. Wutz, M., Hermes, M., Winter, V. & Köberlein-Neu, J. Factors influencing the acceptability, acceptance, and adoption of conversational agents in health care: integrative review. *J. Med. Internet. Res.* **25**, e46548. <https://doi.org/10.2196/46548> (2023).
61. Zhang, J., Ma, Y., Zhang, H., Chen, Y. & Yu, J. Predicting older adults smart healthcare adoption using an extended TAM. *Sci. Rep.* **15** (1), 37486. <https://doi.org/10.1038/s41598-025-21419-2> (2025).

## Figures

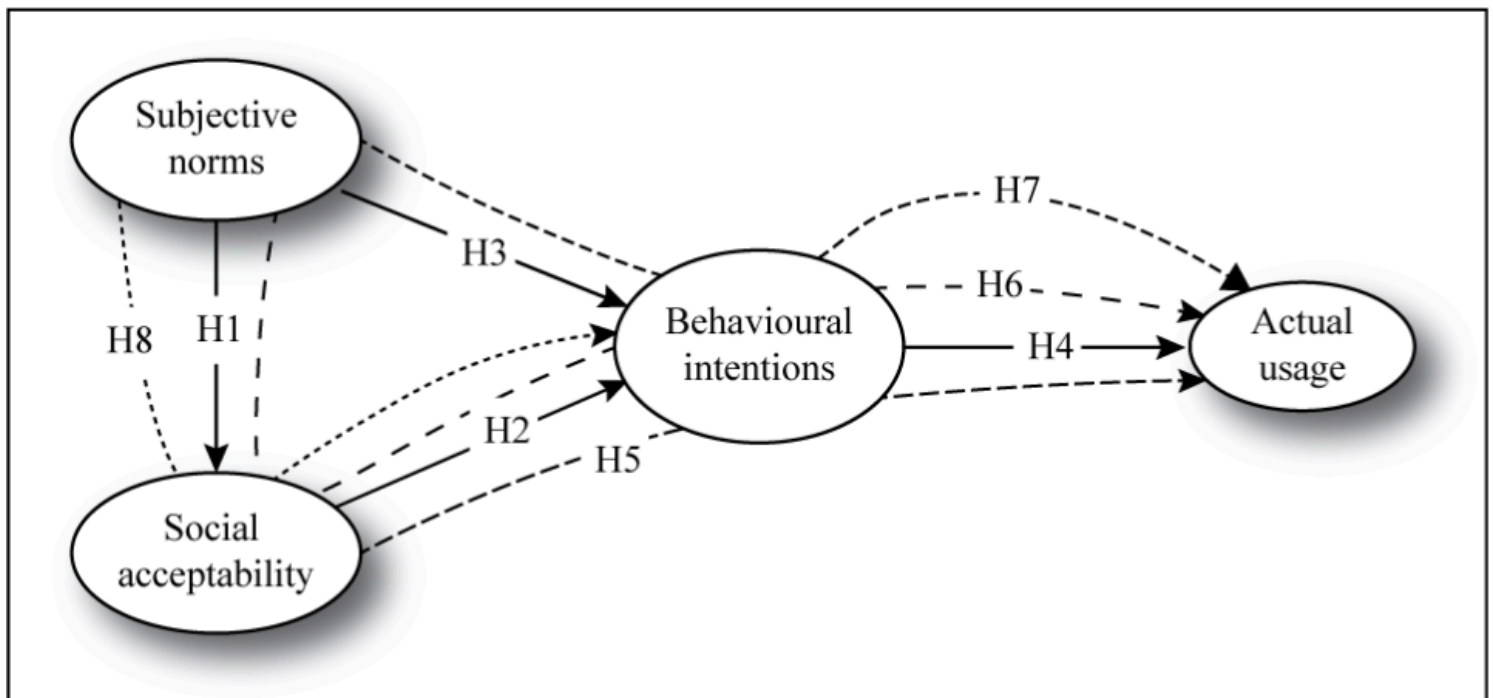


**Figure 1**

The hierarchical structural model.

## Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- [SupplementaryFileA.docx](#)
- [SupplementaryFileB.docx](#)
- [SupplementaryFileC.xlsx](#)
- [SupplementaryFileD.docx](#)
- [SupplementaryFileE.docx](#)