How does a Proactive Approach to Life influence the Acceptance and Use of Patient-Generated Health Data?

Abstract

Measuring the effects of proactivity on the acceptance of patient-generated health data (PGHD) through the Unified Theory of Acceptance and Use of Technology (UTAUT) represents a crucial area of research in the field of mobile health (mHealth) technologies. This study focuses on understanding how proactive behaviors influence health professionals' acceptance and use of PGHD, which is increasingly pivotal for improving healthcare delivery and patient engagement. The integration of PGHD into clinical practices has the potential to transform patient care by fostering personalized treatment strategies and enhancing communication between patients and healthcare providers. The significance of this topic is underscored by the rapid evolution of Health technologies, especially highlighted during the COVID-19 pandemic, which has accelerated the adoption of digital health solutions. Despite the growing reliance on mobile applications for health management, hesitance persists among healthcare professionals regarding the promotion and utilization of these technologies, impacting their effectiveness in improving patient outcomes. The UTAUT model, which examines factors like performance expectancy and social influence, provides a framework for analyzing the behavioral intentions of health professionals towards PGHD, indicating a need for further investigation into these dynamics.

Introduction

Theoretical Background

PGHD refers to health-related information that individuals collect, record, or share about their own health conditions, lifestyle, or well-being, often outside of clinical settings (Technology, 2023). Unlike traditional medical records maintained by healthcare professionals, PGHD is actively gathered by patients themselves using wearable devices, mHealth applications, smart sensors, or self-reported surveys. Examples of PGHD include activity levels, heart rate data, blood glucose measurements, dietary intake, sleep patterns, and even mental health tracking (Khatiwada et al., 2024; Technology, 2023). The growing accessibility of digital health technologies has made PGHD an increasingly significant factor in modern healthcare (Khatiwada et al., 2024).

The adoption of PGHD has been steadily increasing with advancements in digital health technologies and telemedicine (Khatiwada et al., 2024; Rosner et al., 2021). Wearable devices such as fitness trackers and smartwatches are now commonplace, enabling individuals to continuously monitor various health parameters (Khatiwada et al., 2024; Technology, 2023). MHealth applications allow patients to log symptoms, track medication adherence, and engage in self-management strategies (Omoloja & Vundavalli, 2021). Additionally, electronic health record (EHR) systems are evolving to integrate PGHD, allowing physicians to use real-time patient data to support clinical decision-making (Khatiwada et al., 2024; Nazi et al., 2024). Despite these developments, challenges remain regarding data accuracy, standardization, security, and the willingness of both patients and healthcare providers to integrate PGHD into routine care (Khatiwada et al., 2024; Rosner et al., 2021).

One of the major benefits of PGHD is its potential to facilitate the early detection of illnesses (Khatiwada et al., 2024; Nazi et al., 2024). Continuous health monitoring allows for the identification of subtle physiological changes that may indicate the onset of a disease before noticeable symptoms appear (Khatiwada et al., 2024). For instance, abnormal heart rate patterns detected through wearables may signal atrial fibrillation, prompting early medical intervention (Nazi et al., 2024). Similarly, fluctuations in blood glucose levels recorded by diabetic patients can help in adjusting treatment plans before complications arise (Omoloja & Vundavalli, 2021). The ability to recognize health risks early can significantly improve patient outcomes and reduce healthcare costs (Khatiwada et al., 2024; Nazi et al., 2024).

PGHD plays a crucial role in shifting healthcare from a reactive to a preventive model (Guardado et al., 2024; Khatiwada et al., 2024; Nazi et al., 2024). By leveraging real-time health data, individuals can take proactive steps to manage risk factors and make informed lifestyle choices (Khatiwada et al., 2024; Nazi et al., 2024). Preventive health measures, such as tracking daily physical activity, monitoring blood pressure trends, and analyzing sleep quality, empower individuals to adopt healthier behaviors (Khatiwada et al., 2024). Additionally, healthcare providers can use PGHD to identify at-risk individuals and implement early intervention strategies, reducing the burden of chronic diseases (Guardado et al., 2024; Nazi et al., 2024; Rosner et al., 2021).

The rise of PGHD contributes to the development of personalized health solutions tailored to individual needs (Khatiwada et al., 2024). By analyzing trends in a patient's data, healthcare providers can design customized treatment plans and recommendations (Demiris et al., 2019; Khatiwada et al., 2024). Machine learning algorithms and artificial intelligence are increasingly being used to process vast amounts of PGHD, enabling more accurate predictions of disease progression and treatment efficacy (Khatiwada et al., 2024). Personalization enhances patient engagement, adherence to medical advice, and overall health outcomes (Demiris et al., 2019; Khatiwada et al., 2024).

PGHD facilitates improved communication between patients and healthcare professionals (Omoloja & Vundavalli, 2021). Traditionally, medical decisions have been based on periodic check-ups and retrospective data (Omoloja & Vundavalli, 2021). With PGHD, clinicians gain access to a continuous stream of real-time data, allowing for more dynamic and informed discussions (Rosner et al., 2021). Patients can share their health metrics remotely, enabling timely feedback from physicians and reducing the need for unnecessary in-person visits (Rosner et al., 2021). This continuous exchange of information fosters a more collaborative approach to healthcare, ultimately leading to better patient satisfaction and medical outcomes (Omoloja & Vundavalli, 2021).

By understanding the importance of PGHD and its implications for healthcare, this paper aims to explore how proactive engagement influences the acceptance and utilization of PGHD, ultimately shaping the future of personalized and preventive medicine (Khatiwada et al., 2024; Omoloja & Vundavalli, 2021).

In the following section the definition of Proactive Personality (PP), its characteristics and the various concepts of proactivity will be explained.

Bateman and Crant (1993) consider a PP as a person's stable tendency to effect change in their environment and at the same time not being restricted by situational forces. In contrast, individuals with a relatively passive personality allow their environment to shape them, just reacting and adapting to external circumstance (Bateman, T. S., & Crant, J. M. 1993).

This proactive tendency is reflected in several key characteristics. These define individuals with a PP and are explained in the following section.

Proactive individuals seek innovative approaches to problem-solving (Leavitt, H. J. 1978). This tendency may stem from their consistent engagement in exhibiting initiative, exploring opportunities, and persevering until meaningful change occurs (Bateman, T. S., & Crant, J. M. 1993; Aryee, S., Srinivas, E. S., & Tan, H. H. 2005; Fay, D., & Frese, M. 2001; Parker, S. K., Bindl, U. K., & Strauss, K. 2010). They are often associated with extraversion, conscientiousness, need for achievement, and need for dominance. However, they show no correlation with openness, neuroticism, agreeableness, locus of control, mental ability, and response bias (Bateman, T. S., & Crant, J. M. 1993; Parker, S. K., Bindl, U. K., & Strauss, K. 2010; Crant, J. M. 1995; Grant, A. M., & Ashford, S. J. 2008).

Conversely, a passive personality exhibits the opposite tendencies. With little drive they rely on others' initiative for changes, adapting to them and accepting the status quo (Bateman, T. S., & Crant, J. M. 1993).

Various concepts have been identified, capturing different characteristics, which will be explained in the following section.

Tornau and Frese (2013) define these concepts as follows:

- **Proactive Personality** (Bateman, T. S., & Crant, J. M. 1993)**:** An individual's stable tendency to effect change in their environment and at the same time not being restricted by situational forces.
- **Personal Initiative** (Fay, D., & Frese, M. 2001)**:** An individual who is actively working on her goals. While overcoming obstacles and setbacks on her way, she proves perseverance and persistence.
- **Taking responsibility** (Morrison, E. W., & Phelps, C. C. 1999)**:** An individual who proactively and voluntarily improves their environment, even when there is no personal benefit.
- **Participation (**Van Dyne, L., & LePine, J. A. 1998)**:** An individual who constructively contributes suggestions to improve processes instead of criticizing shortcomings.

Tornau und Frese (2013, 2015) conducted a scientific analysis and found correlations between these four concepts. Both PP and Personal Initiative exhibit intercorrelations and strong connections to the Big-Five personalities. Additionally, personal initiative, taking responsibility and participation are significantly correlated.

Given these interrelations, the study of PP has gained increasing academic attention. This increasing awareness will be further explained in the following section.

Beyond the Big-Five personality traits, research focused on PP as a distinct field (Fuller Jr, B., & Marler, L. E. 2009). In particular, the relation of openness to experience, extraversion, conscientiousness, and neuroticism to PP has gained attention (Fuller Jr, B., & Marler, L. E. 2009).

To sum it up, a proactive individual approaches situations different from before, resulting in new achievements, taking on responsibilities or going beyond their responsibilities (Kauffeld, S., & Spurk, D. (Eds.). 2019).

Unified Theory of Acceptance and Use of Technology

The UTAUT, introduced by Venkatesh et al. (2003), offers a comprehensive model for understanding the factors that influence technology adoption and actual usage as reflected in the behavioral intention (BI). By integrating elements from earlier technology acceptance models, it identifies four primary determinants that shape BI and actual usage:

1. Performance Expectancy (PE) – This refers to the degree to which individuals believe that using a particular technology will improve their performance. It is often considered the strongest predictor of technology adoption and is influenced by perceived usefulness, expected benefits, and efficiency gains (Venkatesh et al., 2003).

2. Effort Expectancy (EE) – This captures the perceived ease of use associated with the technology. Technologies that require less cognitive effort or technical skill tend to be adopted more quickly, especially among individuals with less digital literacy. This factor is closely related to perceived ease of use in the Technology Acceptance Model (TAM) and is particularly relevant when introducing new systems to non-technical users (Venkatesh et al., 2003).

3. Social Influence (SI) – This determinant reflects the extent to which individuals perceive their important others expect them to use a given technology. Social norms and peer recommendations can play a crucial role in adoption, particularly in workplace settings or communities where collective behavior shapes individual decision-making (Venkatesh et al., 2003).

4. Facilitating Conditions (FC) – This refers to the presence of organizational, technical, or infrastructural support that enables technology adoption. It includes aspects such as access to training, device compatibility, and availability of customer support (Venkatesh et al., 2003). Even if technology is perceived as useful and easy to use, adoption may be hindered if users lack the necessary resources, such as stable internet access or technical assistance.

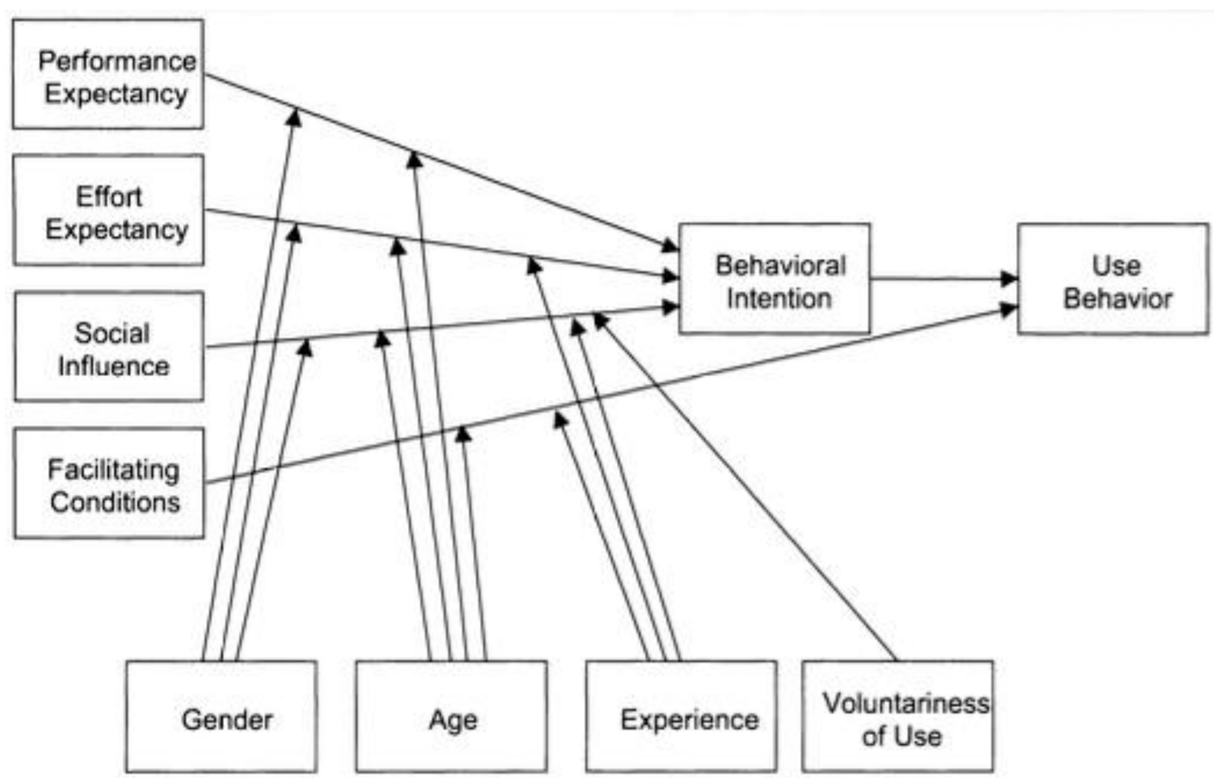

Figure 1. UTAUT Model (Venkatesh et al., 2003)

This paper integrates the UTAUT model with the concept of PP to explore how individual disposition influences technology adoption, as detailed in the following section.

In 1993 the first Proactive Personality Scale (PPS) was published by Bateman and Crant. Initially, 47 attributes were selected to determine PP. Out of these, 27 were analyzed using a first data sample. To gain homogeneity and concision within the survey, 10 unreliable items were removed (Bateman, T. S., & Crant, J. M. 1993).

The final PPS included 17-items each using a 7-point Likert Scale. This scale demonstrated strong reliability in three different data-samples (Bateman, T. S., & Crant, J. M. 1993).

Since then, several abbreviations of this 17-item PPS were published. These shortened versions were constructed using the items with the highest loadings (Claes, R., Beheydt, C., & Lemmens, B. 2005). The following table provides an overview of the PPS surveys, their questions and their Cronbach's alpha scores, along with the authors.

The 4-item scale is a subset of the 6-item scale, which, in turn, consists of items from the 10-item scale. The 5-item scale shares only three items with the 10-item scale. Both Kickul & Grundy (2002) and Seibert et al. (1999) proofed a high correlation between the original 17-item scale and the 6- and 10-item versions.

For the survey of this paper the 6-item scale was selected. The main reason for this is the high Cronbach alpha value and the restriction to a maximum of 6 questions for the topic of PP. Since the 6-item scale is a subset of the 10-item scale and both have a high alpha value, it underlines the validity of the 6-item scale. The 5-item scale was not taken into consideration because of the exceptional high alpha value in comparison to the other scales. Tavakol, M., & Dennick, R. (2011) state that a high alpha score can be the result of a low variance in the sample or items within the scale, correlating too strongly.

Importance of the Research Question

The acceptance of PGHD is a critical factor in the successful integration of digital health technologies into modern healthcare systems. Understanding the role of proactivity in this context is essential because healthcare providers and patients must engage with these technologies actively to realize their full potential. Proactivity, which involves taking initiative in health monitoring and self-management, can influence key determinants of technology adoption, such as perceived usefulness, ease of use, and SIs. However, current research has not sufficiently addressed how a proactive approach affects healthcare professionals' and patients' willingness to adopt PGHD solutions.

With the rapid digitalization of healthcare, particularly following the COVID-19 pandemic, the need for real-time, patient-driven data has become increasingly evident. PGHD has the potential to improve early disease detection, enhance preventive care, and facilitate personalized treatment plans. Despite these benefits, many healthcare professionals remain hesitant to incorporate PGHD into their clinical workflow due to concerns about data reliability, security, and additional workload. Investigating the role of proactivity in overcoming these barriers provides valuable insights into how to encourage broader acceptance of PGHD and ensure its effective utilization.

By applying the UTAUT, this study aims to analyze how proactive behaviors impact factors such as PE, EE, SI, and FC in the adoption of PGHD. The findings of this research could inform the development of targeted interventions and policies aimed at increasing the adoption and meaningful use of PGHD, ultimately contributing to improved patient outcomes and more efficient healthcare systems.

The above-mentioned reasons lead to the following research question (RQ) of the paper:

RQ: How does a Proactive Approach to Life influence the Acceptance and Use of Patient-Generated Health Data?

Hypotheses

To understand the factors influencing the acceptance and use of PGHD, this study builds on the UTAUT framework. We investigate the roles of proactivity and technical affinity as individual characteristics that may affect key UTAUT determinants, including PE, EE, SI, and FC.

Proactivity is a personality trait characterized by an individual's tendency to anticipate and act upon opportunities rather than passively reacting to situations. Proactive individuals seek out new technologies, solve problems independently, and adapt quickly to change, which may shape their perception of PGHD. The following hypotheses examine how proactivity influences key acceptance factors:

Hypothesis 1 (H1): A proactive lifestyle positively influences the perceived PE of PGHD.

Proactive individuals tend to seek out opportunities and anticipate benefits from technology adoption (Bateman & Crant, 1993; Crant, 2000). They actively look for ways to improve their performance and recognize the advantages of using PGHD to optimize healthcare decisions (Crant, 2000). As they take an active role in their health management, they are more likely to perceive PGHD as useful and performance-enhancing.

Hypothesis 2 (H2): A proactive lifestyle reduces the perceived EE associated with PGHD.

Proactive individuals are knowledge seekers and problem solvers who engage in anticipatory actions to acquire the necessary information to use new technologies effectively (Bateman & Crant, 1993; Major et al., 2006; Parker et al., 2010). Their confidence in handling new tools makes them less concerned about the complexity of PGHD, thereby lowering their perceived EE.

Hypothesis 3 (H3): A proactive lifestyle lowers the perceived SI on the acceptance of PGHD.

Proactive individuals actively shape their social environments to align with their goals and values (Seibert et al., 1999). They are less likely to depend on external validation and more inclined to adopt PGHD based on their own perceived benefits rather than social pressure.

The hypotheses proposed for proactivity are depicted in Figure 2.

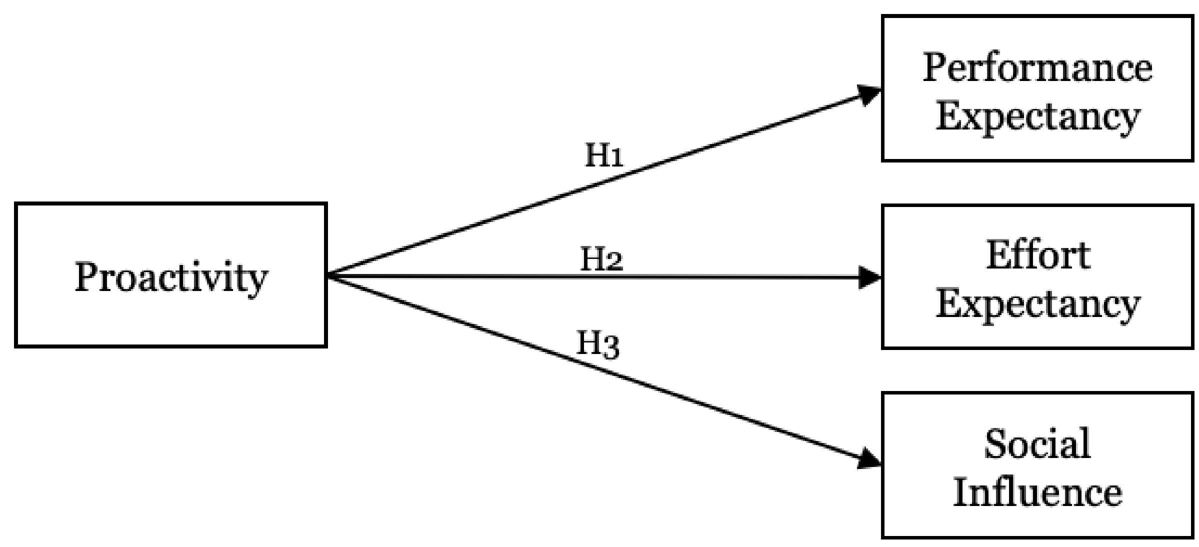

Figure 2. Proposed Model Hypothesis Formulation

Technical affinity refers to an individual's comfort level and familiarity with digital tools and technological ecosystems. Those with high technical affinity are generally more inclined to explore, adopt, and integrate digital health solutions into their routines. The following hypotheses assess how technical affinity impacts the perception of PGHD in terms of usefulness, ease of use, and accessibility.

Hypothesis 4 (H4): Technical affinity positively influences the perceived PE of PGHD, leading to greater acceptance.

Individuals with high technical affinity tend to perceive new health technologies as beneficial tools for improving efficiency and performance (Zhang et al., 2023). Their familiarity with technology makes them more confident in PGHD's ability to enhance clinical workflows and healthcare decision-making.

Hypothesis 5 (H5): Technical affinity reduces the perceived EE associated with PGHD, making it easier to use and integrate.

Users with high technical affinity are more comfortable with digital tools and require less effort to learn and use new health technologies (Diel et al., 2023). This reduces the perceived EE associated with PGHD, encouraging greater adoption.

Hypothesis 6 (H6): Technical affinity enhances the perception of FC, increasing the likelihood of PGHD adoption.

Technically inclined individuals are more likely to identify and utilize the necessary resources, infrastructure, and support systems for adopting new technologies (Zhang et al., 2023). Their familiarity with technology ecosystems allows them to better navigate PGHD integration in healthcare settings.

The hypotheses proposed for technical affinity are depicted in Figure 3.

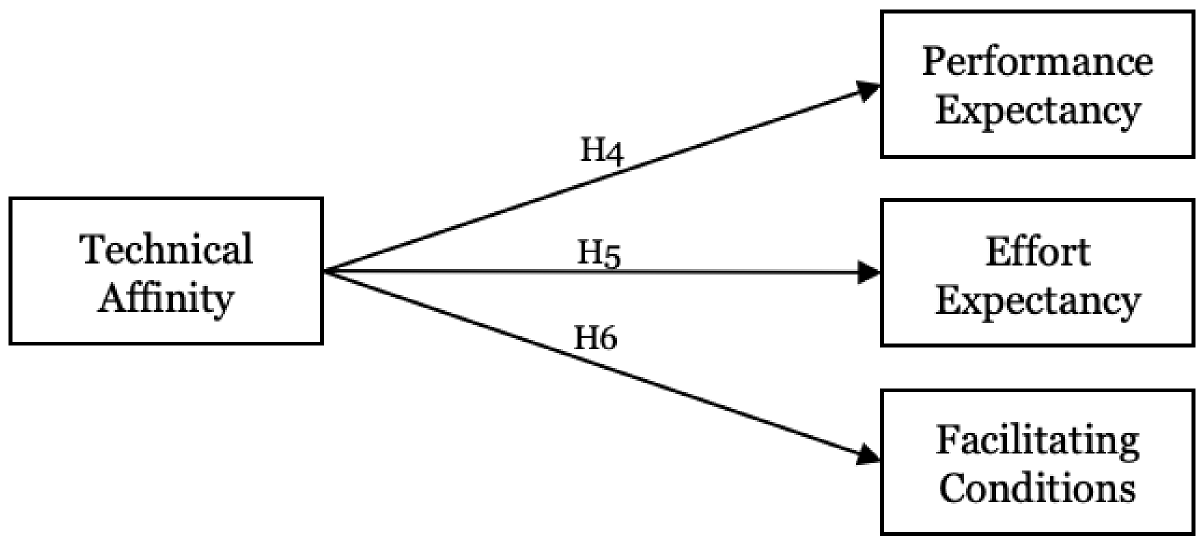

Figure 3. Proposed Model Hypothesis Formulation

Research Method

This chapter explains the research method conducted in this paper. Firstly, the design of the survey will be discussed followed by the data collection process. At the end of this chapter there, the data cleaning and data analysis will be explained.

Between December and February, data for this study was collected through a single-stage online survey. Following a quantitative research approach, a structured questionnaire was designed, consisting of nine sections with a total of 66 questions. The survey primarily focused on UTAUT in relation to mental health app adoption, along with demographic insights. Additionally, six questions were directly related to PP traits, utilizing the 6-item PPS.

The participants in the survey were primarily university students and employees. Out of 251 completed questionnaires, 188 were valid for further analysis, which is a response rate of 75% valid answers. The validity was based on an attention check and the excluding participants with an age higher than 30 and lower than 18. Most of the participants, within the 18-30 age range, were in their early twenties.

As shown in Table 2, the gender distribution was nearly equal, with 44% identifying as female and 56% as male. Since most respondents are students, more than half reported an income lower than 25.000€. The demographic data do not always sum to 188 as respondents were allowed to skip certain questions.

Literature does not provide a standardized interpretation of the PPS scores, therefore the average score of all valid answers was taken as a reference. Participants scoring above the average of 4.9 out of 7 were categorized as having a PP, while those scoring 4.9 or lower were classified as more passive. In total, 59% of the participants scored above the average, indicating a PP, whereas 41% scored average or lower, suggesting a more passive personality.

Variable	Frequency Count	Percentage
Age		
18	1	0.5%
19	6	3.2%
20	10	5.3%
21	27	14.4%
22	38	20.2%
23	30	16.0%
24	19	10.1%
25	17	9.0%
26	13	6.9%
27	11	5.9%
28	9	4.8%
29	5	2.7%
30	2	1.1%
Gender		
Male	106	56.4%
Female	82	43.6%
Jobstatus		
Student	131	73.2%
Parttime	12	6.7%
Fulltime	26	14.5%
Selfemployed	2	1.1%
Retirement	1	0.6%
Unemployed	7	3.9%

Table 2. Demographic Data

The questionnaire also includes additional demographic and moderator data. However, we did not mention them here as they are not relevant to how a proactive approach to life influences the acceptance and use of PGHD.

Analytical Tooling and used Methods

The section highlights the core functionalities of SmartPLS, focusing on two key features: the Partial Least Squares Structural Equation Modeling (PLS-SEM), which evaluates complex relationships between constructs, and bootstrapping, a resampling method used to estimate the significance of path coefficients.

PLS-SEM Path Model Development

Based on the definition of the hypothesis and the UTAUT model the PLS-SEM Path-Model was created as shown in Figure 5. The indicators are labeled with the short form of the corresponding construct and sequential number. All constructs of the model are reflectively measured, meaning that the measures are effects of an underlying construct. The causality flows from the construct to its measures.

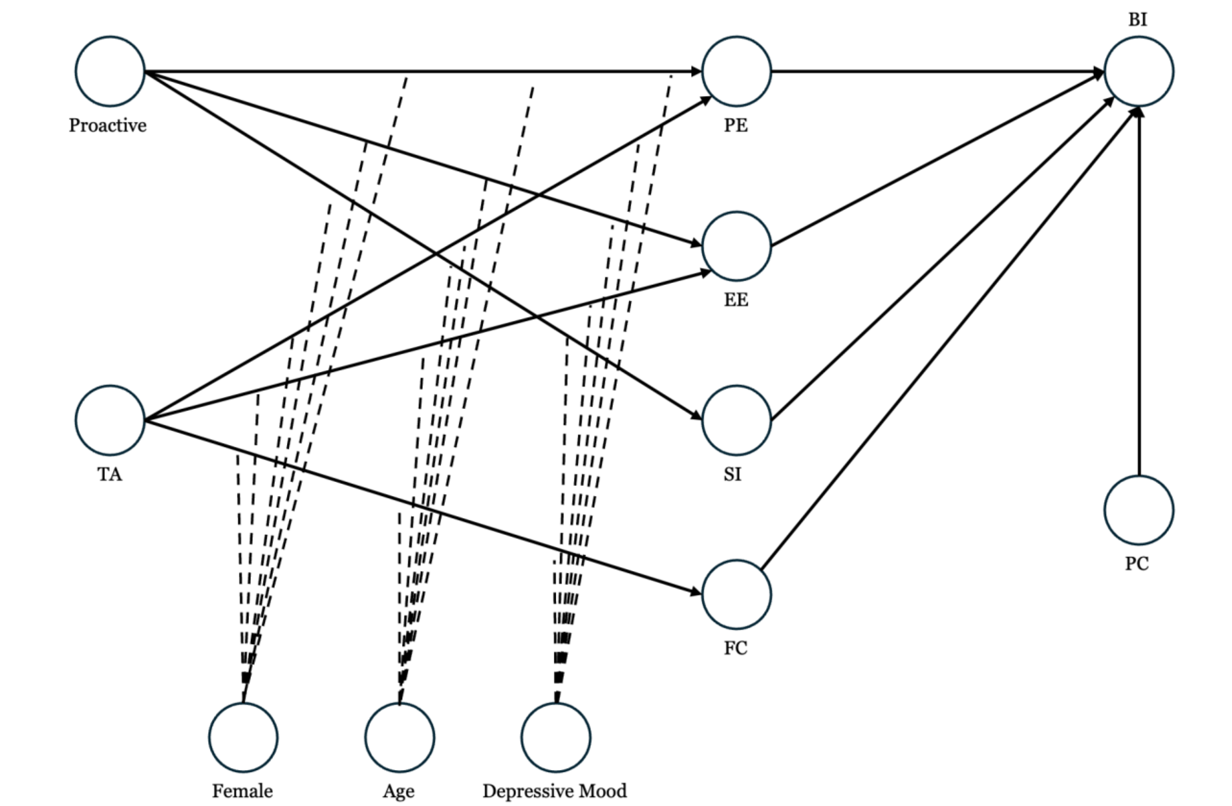

Figure 5. Initial PLS-Path Model

Results

This section presents an evaluation of the results from the initial model. As outlined earlier, the assessment includes analyzing the PLS-SEM results, Cronbach's alphas, and the R^2. Following this, the bootstrapping outcomes are reviewed, and necessary updates are made to the initial model.

Quality Criteria

Cronbach's Alpha is the first criterion evaluated in PLS-SEM, measuring reliability based on intercorrelations of observed indicators. Values between 0.70 and 0.90 are generally considered satisfactory, reflecting good internal consistency. The Cronbach Alpha for TA falls below the threshold with 0.593. Removing TA3, TA6, and TA8 increases Cronbach's Alpha to 0.919, as shown in Table 3. Additionally, the model achieved an R^2 value of 0.512, indicating that 51.2 % of the variance in the dependent variable is explained by the independent variables.

	Cronbach's Alpha	Number of values
Proactive	0,891	6
Depressive Mood	0,836	2
TA	0,919	6
PE	0,787	3
EE	0,854	4
SI	0,930	3
FC	0,776	3
BI	0,897	5
PC	0,951	15

Table 3. Cronbach's Alpha Results on initial PLS-Path Model

Model Estimation

In the following section, the path coefficients of the model are analyzed. Bootstrapping with 5,000 subsamples was conducted, providing the p-values of the path coefficients, as shown in Table 4. The effects of the moderators Female, Age, and Depressive Mood on the model relationships were also examined. As indicated in Table 4, within the initial path model, only the relationships TA → FC and PE → BI are highly significant ($p < 0.001$). Regarding the moderators, Female does not exhibit any significant influence on the model's relationships. Age shows a positive significant effect on Proactive → EE ($p = 0.013$) and a negative significant effect on TA → EE ($p = 0.017$). Depressive Mood (DM) has a positive significant effect on Proactive → SI ($p = 0.014$). Based on these results, the model can be refined by removing all non-significant moderator effects, leading to the updated version of the PLS-Path model presented in Figure 6. The path coefficients and their corresponding p-values are displayed along the connecting lines. Solid arrows represent direct effects between constructs, while dotted lines indicate moderating effects. While the TA → FC relationship remains significant, Proactive → PE is also found to be positive significant ($p = 0.019$).

	Path coefficients	p-Values	*p < 0,05*
Proactive -> PE	0,136	0,362	No
Proactive -> EE	0,190	0,203	No
Proactive -> SI	0,007	0,957	No
TA -> PE	0,135	0,338	No
TA -> EE	0,281	0,105	No
TA -> FC	0,411	0,000***	Yes
PE -> BI	0,644	0,000***	Yes
EE -> BI	0,100	0,106	No
SI -> BI	0,068	0,233	No
FC -> BI	0,016	0,797	No
PC -> BI	0,091	0,130	No

Table 4. Model Estimation Results of PLS-Path Model

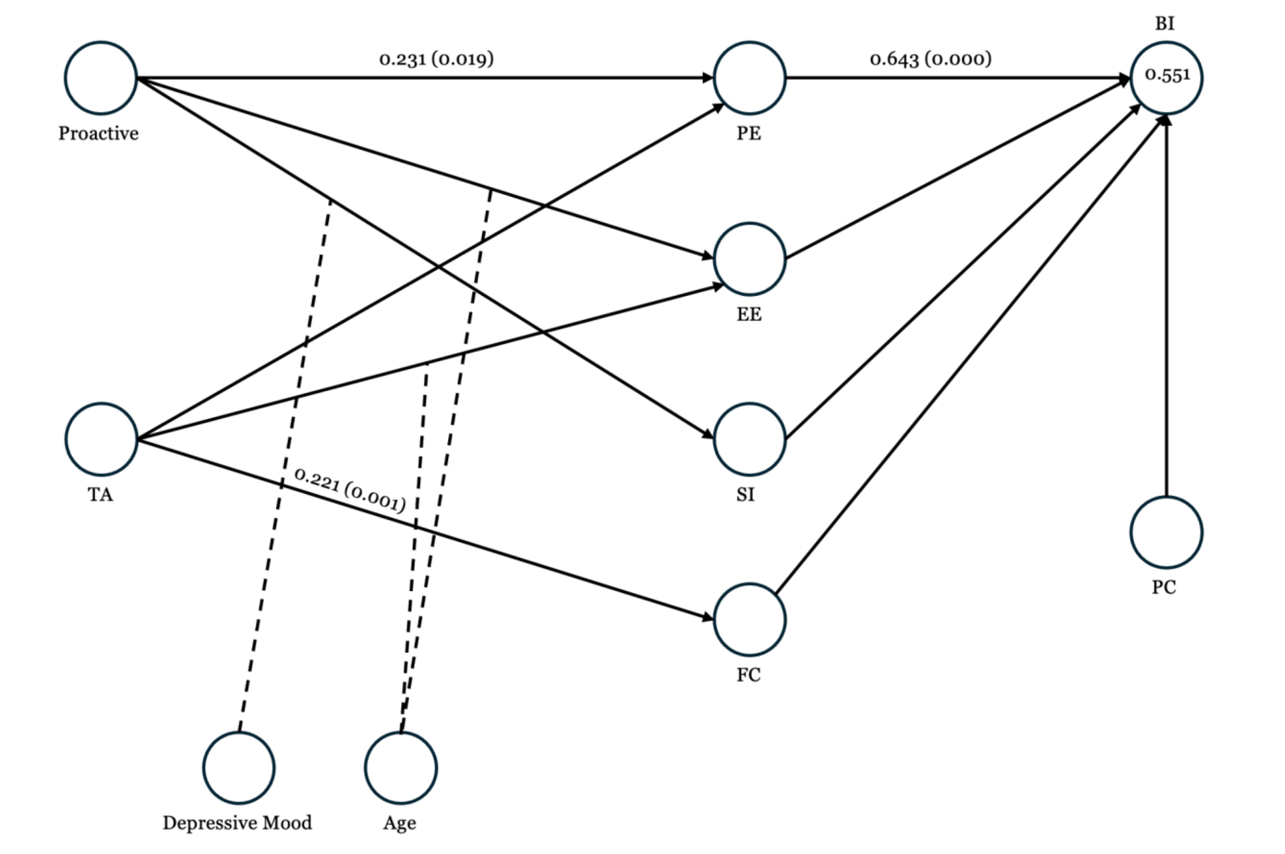

Figure 6. Updated PLS-Path Model with significant Path Coefficients and p-values

Discussion

Summary of Results

The objective of this study was to analyze the relationship of a proactive lifestyle on the UTAUT constructs within a PLS-SEM model. The study employed a descriptive statistic, the PLS-SEM algorithm, and bootstrapping to evaluate the structural model and its reliability. With the PLS-SEM algorithm and the obtained Cronbach's Alpha values ranging from 0,776 to 0,919, indicating generally acceptable internal consistency. However, the initial reliability of Technical Affinity (TA) was below the threshold (0,593), leading to the removal of TA3, TA6, and TA8, which increased its value to 0,919. The R^2 value of 0,512 implies a moderate explanatory power. The bootstrapping results further assessed the significance of path coefficients. The results showed that TA has a positive significant impact on FC and that PE has a positive impact on BI. Most other relationships did not reach a statistical significance. Moderator analysis indicated Female had no significant impact on the model relationships. The updated PLS-Path Model was refined by removing non-significant moderator effects. The analysis confirmed that Technical Affinity and FC remained significant, while Proactive now shows a significant impact on PE.

Key Findings

The results of this study provide important insights into the role of a proactive lifestyle within the UTAUT framework. The findings partially support our hypotheses, demonstrating that proactive behavior strengthens PE but do not provide strong evidence for its weakening effect on EE or SI. Additionally, the results indicate that Technical Affinity has a significant positive influence on FC.

Proactive Lifestyle and Performance Expectancy

As hypothesized, the results show that a proactive lifestyle positively influences PE. This finding aligns with previous research, which describes that a proactive individual has the tendence to effect change in their environment and at the same time not being restricted by situational forces (Bateman, 1993, . 103-118). Because proactive individuals actively seek solutions and adapt to new systems efficiently, they are more likely to perceive a high-performance benefit when using technology. This supports the idea that people who take initiative are more likely to believe that technology enhances their productivity and effectiveness.

Proactive Lifestyle and Effort Expectancy

Contrary to our hypothesis, the results did not have a significant negative relationship between a proactive lifestyle and EE. While we expected that proactive individuals would perceive less effort in learning new system, that data does not support this assumption. A possibility could be that even highly proactive individuals still acknowledge the effort required to adapt to new technology.

Proactive Lifestyle and Social Influence

Similarly, our hypothesis that a proactive lifestyle weakens SI was not confirmed by the results. A possible explanation could be that, even if proactive individuals are self-driven, they still recognize external validation when adopting a new technology.

Technical Affinity and Performance Expectancy

Unlike prior studies, we could not find significant results regarding Technical Affinity and PE. This suggests that technical affinity alone may not be a decisive factor in shaping PE. A possible explanation could be that individuals with technical affinity are comfortable with the technology itself, but their expectations regarding performance benefit are influenced by additional factors.

Technical Affinity and Effort Expectancy

Users with high technical affinity are generally more comfortable with digital tools and require less effort to learn and use new technologies (Diel et al., 2023). However, results did not confirm this hypothesis, as Technical Affinity had no significant influence on EE. One possible explanation is that while technical affine users are comfortable with technology, the perceived effort required to use PGHD may depend on additional factors, such as system complexity, or prior experience with similar platforms.

Technical Affinity and Facilitating Conditions

A key finding of the study is that TA has a significant positive impact on FC. This also is supported by prior studies (Diel et al., 2023). A possible explanation could be that individuals who are comfortable with technology feel more confident in their ability to find solutions, use available resources effectively, and integrate new tools into their workflow.

Theoretical Contribution

This study contributes to existing research by applying the UTAUT model to examine how a proactive approach to life influences the acceptance and use of PGHD. While prior studies have explored PGHD adoption and its role in digital healthcare, limited research has investigated the specific impact of PP traits on technology acceptance. This study addresses this gap by incorporating the PPS and existing knowledge of MHA into the analysis.

A key theoretical advancement of this work lies in its exploration of how proactive individuals perceive and engage with PGHD. By integrating proactivity as a moderating factor, this study examines its influence on established UTAUT constructs, particularly PE and FC. Unlike traditional research that primarily focuses on technological factors, this study highlights the role of individual disposition in shaping technology acceptance. By extending the UTAUT model to include proactivity and technical affinity, this research offers a novel perspective on the factors influencing PGHD adoption. These findings provide a foundation for future studies exploring the intersection of personality traits and digital health technology, paving the way for targeted strategies to improve user engagement and technology acceptance.

Practical Contribution

The key findings of this study provide valuable insights for developers, healthcare providers, and policymakers, helping them improve the adoption of PGHD among both proactive and less proactive individuals. Firstly, healthcare providers and app developers can design features that encourage proactive individuals to leverage PGHD more effectively. This could be done by implementing user-focused features such as a progress-tracking dashboards. Proactive individuals are goal-oriented, and visualizing progress can motivate them by reinforcing their achievements and encourage them to continues use. Additionally, goal-setting functions and personalized feedback can further enhance engagement by aligning with their intrinsic motivation to take control of their health. Moreover, adding insights into PP traits can help tailor personal behavior and increase PGHD adoption. Self-monitoring tools could be effective achieving motivation to take control of one's health. Lastly, healthcare organizations can leverage proactive individuals by highlighting the benefits of PGHD adoption.

Limitations and Future Research

Our study contains several limitations among various dimensions. Due to the inclusion of multiple moderating variables, the survey consisted of 66 questions. Firstly, this led to response rates in the range of 30%-60% (Watson, R., McKenna, H., Cowman, S., & Keady, J. (Eds.). 2008). Additionally, participants might not have maintained the highest level of attention throughout the survey, particularly towards the end, where the PPS was assessed.

Secondly, it was not possible to verify whether participants completed the survey themselves or had assistance from someone else. This factor could influence the model’s results and its implications. Addressing this issue is challenging as detecting and quantifying its occurrence is difficult.

Thirdly, measuring an individual’s PP through self-assessment comes with additional challenges. Respondents may overestimate their abilities, leading to skewed results. This bias could be mitigated by evaluations from a second observer.

Fourthly, the small sample primarily consisted of students in their early twenties with an income below 25.000€. This leads to an overrepresentation of this demographic. Consequently, the results cannot represent and generalize to the broader population (Andrade, C. 2020). Previous studies had similar limitations by focusing on individuals from a single company within one country (Claes, R., Beheydt, C., & Lemmens, B. 2005), undergraduate students (Bateman, T. S., & Crant, J. M. 1993) or MBA students (Bateman, T. S., & Crant, J. M. 1993).

Future research could explore cultural and national differences and their effects on PP to gain valuable insights into how different cultures and nations accept and use PGHD. Additionally, differences across job sectors may influence acceptance and usage of PGHD. Particularly, professions related to IT and Healthcare may yield interesting results. Furthermore, investigating the impact of different family situations on PGHD acceptance and usage could provide valuable insights, as well.

Moreover, given the finding that PP increases the PE and reduces the EE, strategies could be developed to enhance PGHD acceptance not only among proactive individuals but also among more passive individuals.

Finally, to validate these findings, a more concise study should be conducted with fewer questions, focusing specifically on UTAUT, PPS and PGHD, to achieve an even higher response rate. Increasing the sample size while addressing the limitations would further strengthen the results.

Conclusion

Overall, the findings suggest that a proactive lifestyle significantly strengthens PE, reinforcing the idea that proactive individuals perceive technology as beneficial for their performance. However, the expected negative effects on EE and SI were not confirmed. Additionally, the study highlights the significant role of Technical Affinity in improving perceptions of FC, indicating that individuals with higher technical familiarity feel better equipped to use technology due to the availability of necessary support and resources.

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