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ORIGINAL RESEARCH ARTICLE

Acceptance of Digital Health and Well-Being: The Development of the UTAUT2-Screener

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Abstract
Extending conventional health and well-being services with technology has proven to be acceptable and effective. However, implementing such technology in routine care requires contextual tailoring to ensure successful uptake. The Unified Theory of Acceptance and Use of Technology (UTAUT2) is an established model with predictors and moderators of intention to use technology and use behavior. The current study aimed to design a concise screener for technology acceptance in the health and well-being field based on UTAUT2 predictors and to provide a preliminary evaluation of the instrument. The 11-item UTAUT2-Screener includes 7 predictors, i.e., performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, and habit, as well as three moderators and behavioral intention. A within-subject repeated measures design was used. Spearman's correlations were used to test the convergent validity concurrent validity, and the test-retest reliability. Analyses on 184 individuals from the general population demonstrated a moderate association with the original UTAUT2 (mean $\rho = 0.63$), with some variability across the subscales. More specifically, facilitating conditions had the weakest, but still moderate association, while hedonic motivation exhibited the strongest correlation. As an instrument with single-item scales, the UTAUT2-Screener is provided for use in contexts where only brief measures are feasible and researchers or clinicians are willing to accept the reduced psychometric robustness that comes with shorter assessments. The screener provides insights into specific barriers for technology adoption and can consequently support the development of tailored acceptance-promoting interventions, hereby supporting the uptake of digital health and well-being services in practice.

Keywords Technology acceptance · Digital mental health · Digital health · Online interventions · Single-item scale

Introduction

The evidence base for digital health and well-being interventions has been expanding over the past decades. These interventions make use of technology, e.g., smartphones, computers, virtual reality headsets, or wearables, in the context of the promotion of health and well-being or the prevention, diagnosis, and treatment of (mental) illness. There is substantial evidence supporting the acceptability and effectiveness of extending and enhancing conventional healthcare practices with technologies (De Witte et al., 2021). However, a significant gap still exists between

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scientific research and practical implementation. Digital health and well-being interventions still have difficulty finding their way to practice (Van Daele et al., 2022; Chong et al., 2022).

Digital Health and Well-Being Implementation

Several factors contribute to a lack of implementation of digital mental health and well-being interventions. The vast majority of current health professionals were trained at a time when digital health and well-being were not part of their standard curriculum (De Witte et al., 2021). Alotaibi et al. (2025) highlighted the relevance of digital competency and reported that inadequate training and lack of infrastructure were major barriers in this respect. Without prior knowledge and experience, it can be challenging to navigate the digital health and well-being landscape, which is characterized by a proliferation of (mental) health applications (Smith et al., 2023). Digital interventions are also often tailored to a specific disorder, patient population, or (in the context of mental health) therapeutic orientation. Examples include virtual reality exposure therapy for specific phobias, smartphone applications for perinatal mental health, and wearable blood glucose monitors. As a result, variability in a practitioner's patient population can result in a time-consuming exploration of digital interventions. Furthermore, successful implementation of digital mental health requires a systems approach including attention to digital health regulation, financial structures in mental healthcare, implementation processes and recipient buy-in (Bond et al., 2023; Connolly et al., 2021). Even when an organization, a professional, or a citizen finds an appropriate application meeting their needs, integrating it into their workflows and activities can prove to be challenging (Van Assche et al., 2022).

Tailoring digital health and well-being interventions to each context and the barriers at play, can be one way of promoting successful uptake in routine care (Vis et al., 2023). Professionals and patients (or other end users) can have certain beliefs and expectations or encounter practical limitations that complicate technology adoption. Barriers may stem from the technology's characteristics or from beliefs about it, e.g., a lack of confidence in a technology's quality and reliability or a lack of expected impact of this technology (Borghouts et al., 2021; Schröder et al., 2017; Tully et al., 2021). Looking beyond the content and characteristics of specific technologies or interventions, previous work has also highlighted barriers relating to ICT proficiency and experience, social influence, and legal and administrative characteristics (De Witte et al., 2021; Borghouts et al., 2021; Tully et al., 2021).

Technology Acceptance Theory

These findings are in line with the Unified Theory of Acceptance and Use of Technology (UTAUT), a theory proposed by Venkatesh and colleagues (2003), which originally aimed to integrate existing technology acceptance models to help managers introduce new technologies in the workplace. Existing theoretical models on which the UTAUT is based, include Theory of Reasoned Action (Fishbein & Ajzen, 1975), the Theory of Planned Behaviour (Ajzen, 1991), and the subsequent Technology Acceptance Models. The UTAUT model was intended to predict behavioral intention and, consequently, user behavior in the context of technology adoption in a work-related setting. These constructs are predicted by performance expectancy (the individual's expected benefits of technology implementation), effort expectancy (the expected efforts to make use of the technology), social influence (the opinions of significant others), and facilitating conditions (the availability of technology, as well as the know-how regarding its use). Each of these aspects plays a part in predicting behavioral intentions and use behavior of technology, moderated by gender, age, experience, and voluntariness of use.

This theory has been adapted beyond workplace contexts, including the digital health field. Philippi et al. (2021) validated the UTAUT theory (with the addition of internet anxiety, but without use behavior) through secondary data analysis in the context of internet and mobile-based treatment interventions for different somatic and mental health conditions. They found strong support for performance expectancy, effort expectancy, and social influence as predictive factors for intention to use these digital health interventions. Internet anxiety proved to be both a significant predictor and a moderator. The most important predictor remained to be performance expectancy, explaining about 46% of the variance in behavioral intention (Philippi et al., 2021). The link between acceptance (i.e., behavioral intention) and usage behavior has been established in this context by other authors, including Bosbach et al. (2023) who showed that technology acceptance predicted a substantial part of the variation in the uptake of an internet-based self-esteem training ($R^2 = 0.360$) and also influenced adherence ($R^2 = 0.108$). Yousef et al. (2021) validated the model in the context of personal health records and added attitude as an additional predictor. Neither Philippi et al. (2021) nor Yousef et al. (2021) observed significant moderating effects for age, gender, and experience.

In 2012, the UTAUT2 was published (Venkatesh et al., 2012), which extended the first UTAUT model to assess acceptance of ICT technology in consumers. Hedonic motivation (pleasure derived from technology use), price value

(cognitive trade-off between technology benefits and monetary costs), and habit (the extent to which behavior has become automatic) were new predictors included in this model. A meta-analyses revealed that habit, performance expectancy and hedonic motivation were the strongest predictors of intention to use technology (Blut et al., 2022). However, adding additional constructs to the model, such as compatibility, can substantially alter the predictive power of model components. The model structure can also show variations based on the technology of interest or cultural differences (Blut et al., 2022). The current study makes use of the UTAUT2 model, which incorporates the UTAUT predictors that are already established in the healthcare field (e.g., Philippi et al., 2021) but also accounts for factors which are relevant when implementing technology on a more voluntary basis (e.g., hedonic motivation) (Fig. 1).

Assessment of Technology Acceptance

Both the 2003 and 2012 UTAUT publications also resulted in questionnaires covering the models. Several other studies have implemented adjusted versions of these questionnaires, mostly tailored to a type of technology, e.g., internet-based interventions for mental health (Ebert et al., 2015) or mHealth for the elderly (Hoque & Sorwar, 2017). An important benefit that the UTAUT questionnaires offer compared to other available technology acceptance instruments is that they provide insight into specific potential barriers. These insights can help to guide implementation efforts. Acceptance-promoting interventions should be designed differently when the target population faces challenges in performance expectancy, as compared to effort expectancy for example. However, this richness goes hand in hand with a substantial drawback. Current UTAUT questionnaires are generally relatively long since each of the predictors is assessed with multiple items. While this can promote questionnaire quality, and this aspect has not hindered research implementations of such questionnaires, our experiences with (research into) technology implementation in health and well-being services suggest that the pressurized health field is less likely to adopt time-consuming questionnaires to understand technology acceptance. The UTAUT questionnaires and their revisions have also shown substantial variations in the reliability of their subscales. While the reliability of the performance expectancy scale has generally been supported, other scales have shown varying performance from excellent to poor (e.g., Ebert et al., 2015, De Witte et al., 2020, Apolinário-Hagen et al., 2018).

To make surveying less time-consuming, single-item measures have been proposed as a potentially valid measurement approach. This improves participant experience (fewer semantically redundant items, reduced repetitiveness and fatigue, increased time-efficiency, and lower burden) and can make them more suitable for vulnerable populations who have difficulty with extended test administration (Allen et al., 2022; Gosling et al., 2003). Another benefit is that single-item scales can also reduce the risk of construct contamination and item ambiguity, as well as lower data processing costs (Allen et al., 2022). However, while some single-item scales appear to perform equally as (or better than) their multi-item counterpart, this is not always the case (Diamantopoulos et al., 2012; Opitz et al., 2025). In

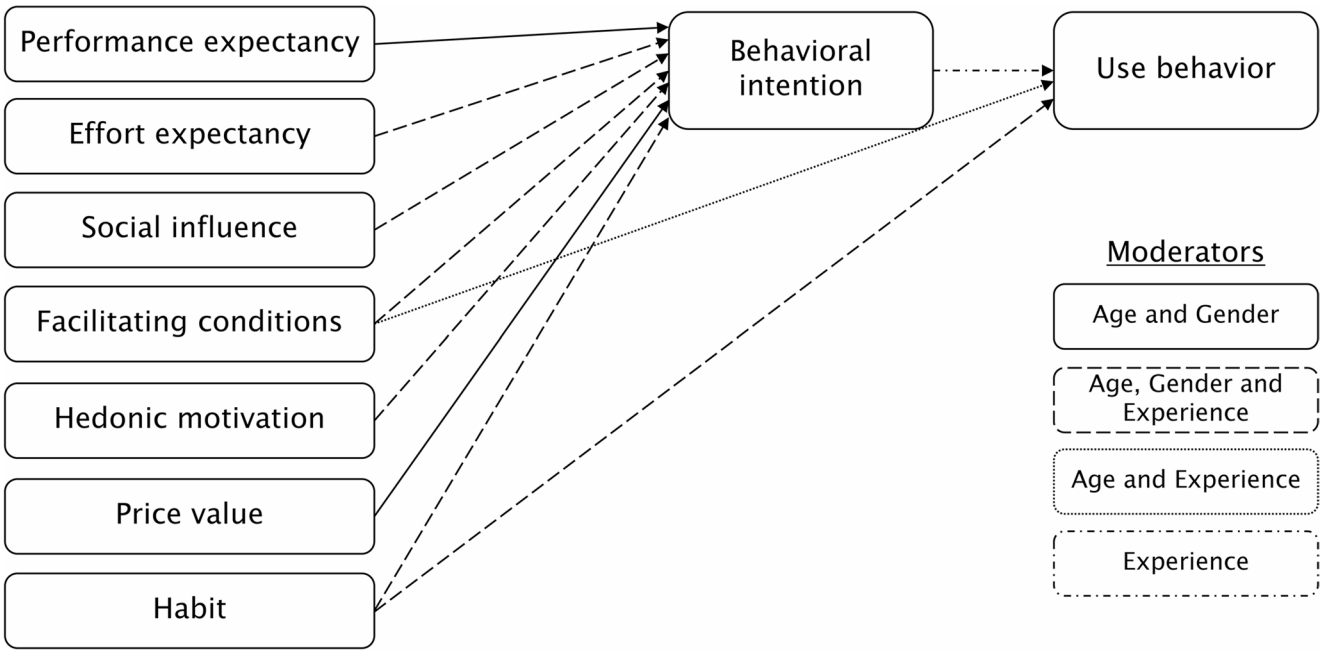


Fig. 1 The UTAUT Model (including the later added additional UTAUT2 predictors) which is the basis of the UTAUT2-Screener

some cases, psychometric evaluation is lacking altogether (Allen et al., 2022). Single-item measures appear most suitable for clearly defined constructs that are narrow in scope. Allen et al. (2022) launched a call to action to publish on (psychometric evaluation of) single-item scales since they are used in practice but rarely thoroughly evaluated.

Study Aims and Hypotheses

The current work, therefore, aimed to develop and test a concise and flexible screener for technology acceptance in the health and well-being field based on the single-item scales of the UTAUT2 predictors. While past questionnaires were generally tailored to one type of technology, the items of the current UTAUT2-Screener aim to accommodate implementations of various technologies (e.g., mHealth, virtual reality) and different user groups (e.g., general population, patients, healthcare professionals) in the field of health and well-being. Data collection in a general population aimed to provide a preliminary evaluation of the convergent validity, the concurrent validity, and the test-retest reliability of the instrument. Thee main study hypotheses were (1) acquiring significant correlations between the UTAUT2-screener and the extended UTAUT2 questionnaire by Venkatesh et al. (2012), showing concurrent validity; (2) observing significant correlations between repeated administrations of the UTAUT2-screener, indicative of test-rest reliability; and (3) attaining a significant positive association between the Performance expectancy item of the UTAUT2-screener and the Optimism scale of the Technology Readiness Index 2, indicative of convergent validity. For convergent validity, no adequate comparison could be found that addressed all UTAUT2-screener predictors so the study focused on Performance expectancy, which is an important predictor that pertains to usefulness of technology in the field of health and well-being.

Materials and Methods

Study Design

The current study was designed to assess whether a single-item screener of the UTAUT2 model showed adequate measurement properties. Therefore, an online survey study was launched through an online recruitment platform. Participants completed the newly developed UTAUT2 screener, the TRI 2 (Parasuraman & Colby, 2014), and the UTAUT-2 questionnaire proposed by Venkatesh et al. (2012). After two weeks, all participants were asked to complete the UTAUT-2 screener again. This study design allowed to gain insight into UTAUT2-screener characteristics and validity.

Before describing study procedures in detail, the method section firstly focuses on the UTAUT2-screener features and development process.

The UTAUT2-Screener

Conceptual Model

The UTAUT2-Screener aims to be a concise instrument that can provide insight into different predictors of intention to use technology. Therefore, it includes all scales and moderators from the UTAUT2 model. Figure 1 provides an overview of the factors of the UTAUT2-Screener, their interrelationships, and moderators of these paths based on the UTAUT2 model. However, it is relevant to note that not all predictors might apply in each context (see also below). The concepts and associations are described in greater detail below based on the work of Venkatesh et al. (2003, 2012). The moderators can affect the different relationships in varying ways, and there can also be an interplay between different moderators within one predictive path.

Behavioral intention refers to the extent to which a professional, patient, or other user intends to use a technology in the future. This concept predicts actual use behavior and is itself predicted by seven determinants, which are detailed below. The UTAUT2 states that the effect of behavior intention on use behavior is moderated by experience, since experience with the technology provides opportunities to reinforce habits. Experience builds routines (resulting in behavior becoming automatic), which can reduce the impact of behavioral intention.

Performance expectancy refers to the extent to which technology can improve performance and is related to its usefulness. Higher scores imply that professionals and end users recognize the benefits of the technology in supporting them in delivering or receiving health and well-being services, which predicts higher behavioral intention. This relation is, however, moderated by age and gender. Extrinsic rewards are more relevant in young individuals. Based on gender schema theory and other work on gender roles, it has been established that masculine roles are more task-oriented hereby making a predictor based on task accomplishment more salient.

Effort expectancy is the degree of ease associated with the use of the technology. When using the technology requires little effort, behavioral intention is greater. Effort Expectancy is suggested to be more salient in feminine roles than masculine roles, hence the moderator gender. Age is a second moderator since increased age is associated with experiencing more difficulty in processing complex stimuli and allocating attention. In terms of experience, effort expectancy is more significant in the early stages of a new behavior.

Social influence is of importance as individuals are generally more likely to show a higher behavior intention when the technology is viewed positively by their environment. The extent to which professionals and end users perceive that important others believe they should use the particular technology is referred to as social influence. It also relates to how they believe others will view them in relation to using the technology, but normative pressure will decrease as increased experience fosters a more instrumental motivation for using technology (instead of a social one). In terms of gender and age, feminine roles and older individuals are suggested to be more sensitive to opinions of others, although this again decreases with increased experience.

Facilitating conditions refer to professionals' and other users' perceptions of the availability of technical infrastructure and resources for using the technology. Having the required devices and resources supporting technology implementation increases both behavioral intention and actual use behavior. In an organizational context (i.e., UTAUT), facilitating conditions are presumed to have little effect on behavioral intentions (showing only direct effects on use behavior) since training and support are invariable over employees, but in a consumer context (i.e., UTAUT2) this factor also holds relevance in predicting behavioral intention. Older individuals can show cognitive and physical limitations requiring support and accordingly, attach greater importance to receiving assistance. Therefore, age is a moderator for both use intention and use behavior. Greater experience is related to greater familiarity and facilitated learning, thereby moderating the influence of facilitating conditions on both outcomes. Gender has been suggested to moderate the effect on behavioral intention since masculine roles are more focused on goal-pursuit, while feminine roles are more focused on the process and might value external supporting factors more.

Hedonic motivation refers to the enjoyment or pleasure derived from using the technology and is an important factor in consumer decision-making. The role of the moderators is linked to individual innovativeness and novelty seeking. Hedonic motivation and innovativeness appear more important for young masculine individuals, hence the moderators gender and age. Increased experience reduces novelty, which makes attractiveness less relevant and pragmatic elements (e.g., effectiveness) more important.

Price Value focuses on the cognitive trade-off between the perceived benefits of the technology and the monetary cost for using it, and also predicts intention to use technology. However, this predictor might not apply to all technology implementations, since not every implementation requires a financial investment from the user (some technologies are offered free of charge, or costs can be covered by organisations or governments). Additionally, users are not always able to estimate product costs effectively. However, when users perceive the intervention as good value for the money, this will increase behavioral intention. Masculine roles are linked to competitiveness and decision-making based on information and heuristics (but also the technology fun factor), while feminine roles are more cooperative, detail-oriented, and can be more careful with money (due to greater involvement with purchasing), which can make them more aware of pricing. These differences can increase with age.

Habit represents a perceptual construct that refers to the extent to which behaviors have become automatic. Habit predicts both behavioral intention and use behavior. Moreover, the predictive role of behavioral intention on use behavior can become smaller with increasing habit. More experience will result in a stronger response to cues triggering the behavior and therefore greater (intended) use. Age and gender can also influence information processing. Older individuals, for example, tend to rely more on automatic behavior, and female roles can be more detail-oriented, which can weaken the effect of habit. This predictor will also not apply to all technology implementations since many technologies have not attained high levels of penetration in health and welfare facilities yet.

Instrument Development

Unlike previous UTAUT questionnaires, each scale is assessed by only one item in the UTAUT2-Screener questionnaire (Table 1). Two approaches exist for developing such instruments: selecting one item from a multi-item scale or developing a new item that covers the essence of the scale (Allen et al., 2022; Gosling et al., 2003). Although some subscales were highly homogenous or at times even semantically redundant, making them ideal for single item generation (Diamantopoulos et al., 2012), other item subscales of the UTAUT2 were not entirely equivalent (e.g., Effort expectancy: 'Learning how to use mobile Internet is easy for me' and 'My interaction with mobile Internet is clear and understandable'). Therefore, we developed new items that cover the breath of the construct in line with Gosling et al. (2003). To develop these single items, two researchers (C1-level English proficiency; NDW, FB) independently identified the main themes of all items of the UTAUT and UTAUT2 questionnaires. As a next step, both researchers attempted to draft one item for each of the main items. In parallel, the same assignment was given to Copilot AI (Microsoft; performed March 2024). Finally, both researchers compared and discussed the new items to achieve consensus. The original UTAUT questionnaire often relied on the conditional tense (e.g., "It would be easy for me to become skillful at …") while the UTAUT2 questionnaire

Table 1 Items of the UTAUT 2 – Screener. The items are scored on a 7-point Likert scale (1 'strongly disagree' – 7 'strongly agree'), unless indicated otherwise

	Item	Determinant
1	This technology would be useful and would help to accomplish things more quickly.	Performance expectancy
2	This technology would be easy to learn, to use and to become skillful at.	Effort expectancy
3	People who are important to me, influence my behavior, or whose opinions I value, think that I should use this technology.	Social influence
4	I have the resources and knowledge or help from others to use this technology.	Facilitating conditions
5	Using this technology is enjoyable or entertaining.	Hedonic motivation
6	This technology is reasonably priced and a good value for money.	Price value
7	The use of this technology has become a habit for me.	Habit
8	When indicated, I intend to use the technology in the future or plan to continue using it frequently.	Behavioral intention
9	I have experience with using this technology in this context. (No; limited; more than limited)	Moderator (experience)
10	I am …. years old.	Moderator (age)
11	How do you identify? I see myself as a … (Man; Woman; Other, that is …; Prefer not to say)	Moderator (gender)

more frequently used the indicative mode (e.g., "It is easy for me to become skillful at …"). Given the limited implementation of technology in healthcare and well-being facilities, it was decided to keep the conditional tense in the UTAUT2-Screener for items 1, 2, and 3. The behavioral intention item (item 8) assesses the intention to use (or keep on using) technology when indicated. Moderators or individual differences (age, gender and experience) are included in the questionnaire (items 9, 10, 11) leading to a total of 11 items. For items 1 and 11, the broader context of the questionnaire, namely health and well-being services, is included in the question as it is important for correct interpretation. The full questionnaire can be found in Appendix A.

The subject of the items, "this technology," can be specified in the instructions of the questionnaire. The instructions of the UTAUT2-Screener are deliberately kept short and neutral with the possibility to specify which technology is being reffered to. Descriptions can consist of general technology descriptions or a specific application with a short, neutral definition in the instructions. The current administration relied on a broad definition of digital interventions: "A digital intervention, in which you can receive information, advice or support through a website, app or online platform. You learn more about complaints or problems, complete a self-test, or carry out assignments.".

Items 1 through 8 are scored on a Likert scale ranging from 1 *'Strongly agree'* to 7 *'Strongly disagree'*. The first seven items each relate to a determinant or potential barrier to technology use and can therefore be interpreted in isolation. In addition, these seven items can also be summed into a total score (range 7–49) that provides insight into barriers and facilitators of technology use present in the current context. The higher this total score, the fewer barriers a participant experiences and the greater the likelihood of successful technology adoption. The remaining items are not included in the total score, but directly focus on behavioral intention (item 8) or important moderators of the relationship between the above determinants and intention to use.

Study Participants

As this represents the first study employing this screener, conducting a formal power analysis and sample size calculation was challenging due to the absence of prior estimates for (intraclass) correlation coefficients. Following recommendations by Polit (2014), the current study aimed to recruit 200 participants for this initial evaluation of the screener. We recruited a gender-balanced general sample of 200 adults from the UK, all of whom declared fluency in English. No further screening occurred for age, education, health status or digital literacy. The participants were recruited via Prolific.com (Palan, & Schitter, 2018),

an online platform for participant recruitment for experiments and surveys. This platform has a pool of registered participants which can be accessed for research participation. Participants get a notification once a potential study becomes available and can subsequently decide on participation. The study was approved by the ethics committee of Thomas More University of Applied Sciences. All data was collected through secure online survey software hosted by the academic institution (QuestionPro software). All participants were presented with an information letter and subsequently provided their online informed consent through this platform prior to participation.

Measurement Instruments

Firstly, the UTAUT2-Screener (including predictors and demographic moderators) was implemented as described above. The current administration relied on a broad definition of digital interventions: "A digital intervention, in which you can receive information, advice or support through a website, app or online platform. You learn more about complaints or problems, complete a self-test, or carry out assignments.".

The UTAUT2 questionnaire was implemented as proposed by Venkatesh et al. (2012) and contains 26 items that assess all predictors included in the UTAUT2-Screener (see above). Internal consistency and reliability of the original UTAUT2 subscales was good and presented in Appendix B (Table B.4). Cronbach's α coefficients ranged from 0.81 to 0.94 for the subscales and were 0.97 for the overall scale.

For concurrent validity of the Performance Expectancy construct, the optimism subscale of the Technology Readiness Index (TRI2; 16 items assessing 4 subscales; Parasuraman & Colby, 2014) was used. This subscale measures participants' anticipated increase in control, flexibility, and efficiency in their lives due to technology. The optimism scale showed a good internal consistency (4 items; $\alpha = 0.82$; $N = 184$).

Procedure

All participants completed 3 questionnaires, and one additional item informing on their education level (to complement the demographic moderator items in the UTAUT2-screener). This occurred in the following fixed order: UTAUT2-screener, TRI2, and, UTAUT2 questionnaires, education level. Although the order of the questionnaires was not randomized to prevent the consecutive administration of both UTAUT2 instruments, the items within each questionnaire were presented in random order. After two weeks, participants were asked to complete (only) the UTAUT-2 screener again in order to assess test-retest reliability. On average, participants completed the first survey in 9 min and the second one in 2 min. The data of the first wave was collected on 28 April and the data of the second wave between 12 and 18 May 2025. Participants received a payment of 2 pounds for the first set of questionnaires and 0.75 pounds to complete the retest. Prior to commencing the survey, all participants provided their informed consent.

Statistical Analysis

Data were screened for missing values and incomplete responses. Participants who did not complete both waves of questionnaires were excluded to ensure a consistent and comparable sample across analyses. Descriptive statistics (medians, interquartile range, and percentages) were calculated for age, gender, education, experience with digital health, and well-being of the sample. For the total scores of UTAUT2-Screener, descriptive statistics (means and standard deviations) and correlations were computed. The total scores are the sum scores of the items.

Normality was assessed using the Kolmogorov–Smirnov test. As shown in Appendix Table B.1, the data were not normally distributed, which is consistent with the ordinal nature of the measures. Therefore, Spearman's rank-order correlations were used to examine convergent validity between the UTAUT2 and UTAUT2-Screener, and concurrent validity between the performance expectancy item and the TRI 2.0 Optimism subscale.Test–retest reliability was assessed using Spearman's correlations between Wave 1 and Wave 2 scores of the UTAUT2-Screener.

As this study represents an initial validation of the UTAUT2-Screener, no subgroup comparisons were conducted. For each correlation analysis, a significance threshold of $p < .05$ was applied and adjusted using a Bonferroni correction to account for multiple comparisons. The strength of the correlations was interpreted using conventional guidelines. All analyses were performed using IBM SPSS Statistics (Version 29.0.2.0).

Results

Descriptives and Exploratory Analysis

Of the 200 recruited participants, sixteen were excluded from the results as they did not participate in the second survey. The final sample therefore consisted of 184 participants who completed both questionnaires without missing any items. The mean age was 45.15 years ($SD = 12.82$, range 20–77). Within our sample, 50.0% identified as male, 49.5% identified as female, and one individual (0.5%) identified outside of the binary spectrum. Regarding education, 63.0%

held a university degree, 34.8% completed high school, and 2.2% finished middle school. They had little experience with using digital health and well-being (*Mdn* = 2; *IQR* = 0).

Participants had an average UTAUT2-Screener total score of 35.06 (*SD* = 6.50, range 7–49) in the first wave and 35.33 (*SD* = 6.47, range 10–49) in the second wave. Their intention to use digital health and well-being varied between 1 and 7, with a median of 5.0 (*IQR* = 1). in the first wave and 5.0 (*IQR* = 1) in the second wave.

Descriptive statistics and Spearman's Correlations of all the UTAUT2-Screener items are reported in Appendix B (Table B.2, Table B.3). In Wave 1, item medians ranged from 4 to 6 and interquartile ranges from 1 to 3; correlations between the behavioral intention item and items representing the predictor constructs ranged from 0.54 to 0.69, with all correlations being significant. In Wave 2, item medians ranged from 4 to 6 and interquartile ranges from 1 to 2; correlations between the behavioral intention item and items representing the predictor constructs ranged from 0.46 to 0.69, and again all correlations were significant.

Concurrent Validity

The concurrent validity was assessed using Spearman's Rho correlations between each item of the UTAUT2-Screener and the means of the different scales of UTAUT2 in wave 1. Additionally, a Bonferroni correction was applied. The results indicated a modest relationship between the UTAUT2-Screener and UTAUT2, with all correlations being significantly different from zero and a mean Rho of 0.63 across all scales (Table 2). Most correlations were moderate, with the correlation for hedonic motivation being high.

Table 2 Medians, interquartile ranges, means, standard deviations, spearman's rho correlations, and 95% confidence intervals for the UTAUT2-screener and UTAUT2 subscale means from wave 1

Construct	UTAUT2-Screener Item Mdn (IQR)	UTAUT2 Subscale M (SD)	ρ	95% CI for ρ
Performance Expectancy	6.0 (1)	5.23 (1.29)	0.61*	[0.50, 0.69]
Effort Expectancy	6.0 (1)	5.34 (1.07)	0.57*	[0.46, 0.66]
Social Influence	4.5 (2)	4.22 (1.39)	0.64*	[0.54, 0.72]
Facilitating Conditions	6.0 (1)	5.36 (0.99)	0.56*	[0.45, 0.65]
Hedonic Motivation	5.0 (2)	4.74 (1.40)	0.73*	[0.66, 0.80]
Price Value	4.0 (1)	4.43 (1.18)	0.69*	[0.60, 0.76]
Habit	5.0 (3)	3.85 (1.48)	0.61*	[0.51, 0.70]
Behavioral Intention	5.0 (1)	4.96 (1.31)	0.62*	[0.52, 0.71]
Mean			0.63	

Note: * All reported correlations were significant after Bonferroni correction, α = 0.05

Test-Retest Reliability

The test-retest reliability was assessed using Spearman's Rho correlations between the items of the UTAUT2-Screener in wave 1 and wave 2. A Bonferroni correction was applied. The results indicate significant correlations ranging from 0.45 for facilitating conditions to 0.64 for hedonic motivation (Table 3).

Convergent Validity

The convergent validity was evaluated using a Spearman's Rho correlation between performance expectancy and the TRI2 Optimism subscale and indicated a moderate positive association, $r_s(182) = 0.48$, 95% CI [0.35, 0.59], $p < .001$.

Discussion

The current study aimed to design a brief screener to gauge relevant determinants from the UTAUT models that can guide implementation efforts. The 11-item instrument includes seven potential predictors, three moderators, and behavioral intention. The UTAUT models have proven to provide relevant insight into barriers for the implementation of digital health (e.g., Philippi et al., 2021). The current findings suggest that a brief screener version correlates significantly with the multi-item scale in a general sample. The size of the observed correlations appears to be in line with previous studies on single-item measures, which observed correlations between 0.5 and 0.8 (Allen et al., 2022; Gosling et al., 2003), However, correlations below 0.7 can be considered below expectations from a psychometric standpoint (Allen et al., 2022). So while it cannot be considered psychometrically equivalent to the multi-item scale, these findings indicate that the UTAUT2-Screener does approximate the extended UTAUT2 and can be useful given the practical advantages that single-item instruments can have for researchers, participants, and clinical practice.

Table 3 Spearman's rho correlations of the UTAUT2-screener administration in wave 1 and wave 2

Construct	ρ	95% CI for ρ
Performance Expectancy	0.58*	[0.47, 0.67]
Effort Expectancy	0.53*	[0.42, 0.63]
Social Influence	0.52*	[0.40, 0.62]
Facilitating Conditions	0.45*	[0.33, 0.56]
Hedonic Motivation	0.64*	[0.54, 0.72]
Price Value	0.60*	[0.49, 0.69]
Habit	0.61*	[0.51, 0.70]
Behavioral Intention	0.60*	[0.49, 0.69]

Note: * All reported correlations were significant after Bonferroni correction, α = 0.05

Validity of the UTAUT2-Screener

The digital health and well-being field can be a challenging context to predict intention to use technology and actual use since it is characterized by more variation in use behavior than other contexts (especially in end users). While preventive technologies can be used perpetually, other digital technologies are only relevant when individuals experience certain (medical) conditions. Therefore, the UTAUT2-Screener frames the use intention in a conditional way ("When indicated, I intend to use the technology in the future or plan to continue using it frequently."). Since the current study used a general sample, few participants may experience actual health needs leading to current use of digital interventions. This also implies that there might be more ambiguity for participants when completing the instrument, which is not ideal for scale validity (Allen et al., 2022). This is in line with the test-retest reliability, which is questionable or at times even poor. Interestingly, we can observe that hedonic motivation performs best both in terms of convergent validity as well as test-retest validity. On the other hand, facilitating conditions received the lowest score on both measures. This could be related to item complexity. While the hedonic motivation item is fairly brief and straightforward, facilitating conditions is more complex and contains two elements ('resources' and 'knowledge or help') which could lead to ambiguity. Facilitating conditions was also conceptualized in the UTAUT2 model as a predictor of intention and behavior, and Philippi et al. (2021) and Blut et al. (2022) have also found facilitating conditions to be a less robust predictor of behavioral intention (in contrast to habit). Salgado et al. (2020) suggested that facilitating conditions might be less relevant for mHealth given the penetration of mobile phones and mobile internet. The scope of the current administration also consisted of ubiquitous technologies, which can limit the significance of this item. Alternatively, participant experiences and beliefs might have altered between the two test administrations, which could have led to an underestimation of test-retest reliability.

The relevance of certain predictors will vary depending on the technology of interest, but also the users (e.g., professionals or patients) and the context of assessment (Blut et al., 2022). In this context, it is also relevant to note that the UTAUT2 was originally developed for a consumer context. Chong et al. (2022) observed that facilitating conditions have less predictive power for use intention and behavior in wearable technologies (as compared to non-wearable technologies), in older participants (contrary to proposed moderator directions), and in countries with high healthcare quality. When implementing the UTAUT models to a new (cultural) context, it is relevant to critically evaluate model components and assess the need of additional predictors or moderators (Blut et al., 2022; De Witte et al., 2024). Age and gender have been suggested to be the minimum moderators to be included (Blut et al., 2022), and are therefore included in this brief screener. However, the meta-analysis of Blut et al. (2022) did show that the addition of other constructs to the UTAUT models can have substantial effects on the role of the UTAUT predictors.

There has been some discussion in the literature regarding the opportunities and drawbacks of single-item measurements (Diamantopoulos et al., 2012; Allen et al., 2022). There can be clear benefits of a single-item version of the UTAUT questionnaire for use in time-limited or practice-oriented settings, such as healthcare institutions that are unwilling to administer lengthy questionnaires. Some items of the UTAUT2 instrument are also semantically redundant, but other subscale items do measure slightly different aspects of the same concept. This is a substantial challenge which we addressed by adjusting items to include these different aspects, in line with Gosling et al. (2003). However, this can introduce a certain complexity in the instrument and cognitive load in the user. Single-item measures can also come at the cost of reduced construct precision. The correlations support the value of the UTAUT2-Screener, but it remains relevant to acknowledge that it is indeed a screener which provides quick insights into potential barriers for technology adoption. Implementing the extended questionnaire can be preferred when the study requires more detailed analyses. Diamantopoulos et al. (2012) also developed guidelines for the selection of single-item or multi-item measures.

Limitations

The current study also has a number of limitations. The UTAUT2-Screener has only been tested in a fairly highly educated general population so far, and further tests of the model should be performed in other (professional and patient) populations. Additionally, future research could investigate potential moderation effects, for example by examining differences in relationships between the screener and the full UTAUT questionnaire across subgroups. While item order was randomized, the order of instrument presentation was not (to avoid presenting both UTAUT2 instruments consecutively), which may have influenced responses to the second UTAUT2 questionnaire. The first 200 participants who met the inclusion criteria and accessed the questionnaire were included. All analyses were conducted on the subsample of 184 participants who completed both waves, in order to maintain a consistent sample size and minimize differences across analyses. Although analyses of convergent and concurrent validity at Wave 1 could have been performed on the full sample of 200 participants, additional analyses indicated that this did not yield different results.

The decision to report only the results based on the 184 participants was made to enhance clarity and readability. Nevertheless, restricting analyses to the smaller sample may have resulted in a loss of statistical power and reduced generalizability of the findings. The use of financial incentives and the experience of time pressure could have contributed to some of the unsatisfactory validity scores. The model might perform better in a more intrinsically motivated patient or professional sample and when the technological intervention is more concrete (e.g., assessing technology acceptance of iCBT treatment in patients with depressive disorders). Chong et al. (2022) suggest that the effects of the UTAUT predictors are stronger in patient populations compared to healthcare professionals, as the latter may have more experience and/or be confronted with the non-voluntariness of use. It is therefore recommended to perform further psychometric evaluations in the future and in other samples. The meta-analysis of Blut et al. (2022) in the field of information systems has proposed that the UTAUT2 model can be extended with four additional factors, i.e., technology compatibility, user education, personal innovativeness, and costs of technology. However, adding these factors can change the predictive power of the established UTAUT constructs, which have been shown to be valuable in the field of health and well-being (e.g., Philippi et al., 2021). while the current study chose to use the original UTAUT2 model, additional items could be added to the instruments when deemed relevant for future implementations. The instruments did not include reverse-scored items, which can help to mitigate response bias. The survey included checks for unreliable responding (e.g., "Please indicate the second option from the right"), but these might have been too obvious, as these items were visually shorter. More subtle checks could have been implemented. Finally, the instrument is currently only available in English, but we aim to work and collaborate on translated versions of the instrument.

Conclusion

To conclude, the current study shows that it is possible to gain insight into several predictors of intention to use digital health and well-being, using a concise instrument. The UTAUT2-Screener includes determinants from the UTAUT2 model applied to a health and well-being context. The UTAUT2-Screener is suitable for use in contexts where only brief measures are feasible and researchers or clinicians are willing to accept the reduced psychometric robustness that comes with shorter assessments. It can be used to gain insight into barriers for technology adoption in relation to different technologies, user groups, and implementation contexts, although previous work has suggested that the predictive power of several determinants can increase or decrease depending on the setting. Insights gained into these specific barriers for technology adoption can aid the development of tailored acceptance-promoting interventions, hereby supporting the uptake of digital health and well-being services in practice. Gaining insight into technology acceptance is one element which could be relevant in addressing current digital health implementation challenges, but this element should be embedded in a systems approach where referral and care pathways, reimbursement schemes, and care organization are critically analyzed (De Witte et al., 2026). While the present study offers first indications of the psychometric properties of the instrument, further research is needed to evaluate its validity in diverse samples, subgroups, and contexts.

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Data availability Data are available upon direct request to the authors. The UTAUT2-screener is provided in Appendix A.

Declarations

Ethics approval The study was approved by the ethics committee of Thomas More University of Applied sciences (reference 2425_3).

Informed consent All participants provided informed consent prior to participation.

Conflict of interest On behalf of all authors, the corresponding author states that there is no conflict of interest.

Clinical trial number Not applicable.

Author area of interest Implementation technology and science, Digital mental health.

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