Original Article

Development and Validation of a Basic Psychological Needs Scale for Technology Use

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Abstract: The aim of this work was to develop a valid and reliable scale to measure Basic Psychological Need Satisfaction for Technology Use (BPN-TU). According to the self-determination theory, satisfaction of the Basic Psychological Needs (BPNs) for Autonomy, Competence, and Relatedness is crucial to well-being and autonomous motivation. Research into the role of BPN Satisfaction in technology use is scarce, partly due to a lack of appropriate measuring tools. To develop a pool of original BPN-TU scale items, we held 10 interviews. Based on these items, we conducted four validation studies with four independent samples (total N = 821), collecting user responses to different technologies: digital voice assistant, exoskeleton, chatbot, and social robot. Good model fit was supported by confirmatory factor analyses for a twelve-item scale, containing three items each for satisfaction of users' Autonomy, Competence, Relatedness to Others, and Relatedness to Technology. The scale was validated in English and German.

Keywords: scale development, technology usage, basic psychological needs, well-being, quantitative methods

Basic Psychological Need Satisfaction is a key factor in explaining people's autonomous motivation (volitional, self-directed motivation) and overall well-being (Deci et al., 2008; Ryan & Deci, 2000a). The basic psychological needs theory (BPNT; Deci & Ryan, 2000; Ryan & Deci, 2000b) is one of six so called *mini theories* forming the self-determination theory (SDT; Deci & Ryan, 1985) that established three universal Basic Psychological Needs (BPNs):

- Autonomy, i.e., feeling control over one's own decisions and actions,
- Competence, i.e., experiencing effectance and mastery of a task, and
- Relatedness, i.e., caring for others and being cared for in return.

Many studies from education (Tian, Chen, & Huebner, 2014; Wang et al., 2019), physical exercise (Balaguer et al., 2012; Gunnell et al., 2014; Li et al., 2013), and work (Deci & Ryan, 2014; Ilies et al., 2017; Williams et al., 2014) contexts have referenced the importance of BPN Satisfaction to people's motivation and well-being.

More recently, BPN Satisfaction has also attracted attention from the technology sector, as some user studies have addressed the importance of users' Need Satisfaction to their intention to use technological devices (see e.g., De Vreede et al., 2021; Jiménez-Barreto et al., 2021; Moradbakhti et al., 2022), revealing that BPN Satisfaction is a good predictor of technology acceptance, even when compared to classic predictors of technology acceptance, such as Ease of Use and Perceived Usefulness (Moradbakhti et al., 2023).

Given the increasing use of technologies in our daily lives, user well-being – to which BPN Satisfaction could significantly contribute in the long-term – should be a key priority of developers (Moradbakhti et al., 2022; Peters, 2023; Peters & Calvo, 2021). In the context of experiments and analyses based on user-centered design, more studies could therefore focus on measures of BPN Satisfaction, specifically, if we acknowledge that technologies in many cases developed to (1) become more autonomous (e.g., autonomous vehicles; K. T. Chen & Chen, 2021), (2) be more efficient and competent (e.g., algorithmic decision systems; Hou & Jung, 2021), (3) replace human contact (e.g., customer service chatbots; Haugeland et al., 2022), and (4) provide new ways of social interaction with others (e.g., social media; Roberts & David, 2020).

The current work introduces a tool for researchers and practitioners to measure BPN Satisfaction in human–technology interaction contexts. Assessing BPN Satisfaction when developing or testing technologies is particularly valuable for practitioners, as the results offer concrete information on technology aspects that can be improved. For example, if a technology scores low on Autonomy Satisfaction, practitioners could improve features related to customization and personalization as they have been proven to enhance users' feeling of autonomy (see e.g., Lau & Ki, 2021; Peng et al., 2012). If a technology scores low on Competence Satisfaction, users could feel that the technology takes away from their own desire for mastery, in this case additional explanations, transparency and demonstrators of positive feedback should be added to allow users to gain better understanding of the technology and associated tasks, to take ownership of accomplishments, and to perceive themselves as competent in the specific context of technology usage (see e.g., van Roy & Zaman, 2019; Zainuddin et al., 2019). If the technology scores low on Relatedness Satisfaction, features of the technology should be added or improved that either foster human connection or a connection to the technology itself (see e.g., Yang et al., 2021).

Across four individual studies with a total *N* of 821, we developed a scale for the assessment of Basic Psychological Need Satisfaction for Technology Use (BPN-TU). The scale does not only follow a strong validation procedure, it was also developed to fit and be easily adaptable to various different technologies and contexts. This makes the BPN-TU scale not only a valuable contribution to the HCI community, it is also applicable to areas of Engineering Psychology, User Experience research, and related fields in both empirical research and practice.

Theoretical Background

In comparison to other domains such as education, physical exercise, or work, the Need for Relatedness comprises two aspects in the context of technology interaction: On the one hand, technologies can mediate people's Need for Relatedness to Others (e.g., communication technology), and on the other, people can also feel relatedness to the technology itself (e.g., companion robot). For example, relatedness to others can be studied in the domain of video gaming when users play online with other human players or cooperatively in the same room using the same console where the technology (here: gaming console) functions as a mediator (see e.g., Johannes et al., 2021; Vuorre et al., 2022). The relatedness to the technology itself, for example, can be imagined to play an important role in social robotics where a humanoid robot is often assumed to be perceived as some kind of *social actor* (see e.g., Leichtmann & Nitsch, 2021; Nass & Moon, 2000). Against the background of technology use, need satisfaction could therefore be divided as follows: Autonomy Need, Competence Need, Need for Relatedness to Others, and Need for Relatedness to the Technology.

Previous research pointed toward the positive influence BPN Satisfaction has on technology use. For example, studies revealed that BPN Satisfaction led to higher acceptance of a chatbot (De Vreede et al., 2021), more positive customer experience with a service chatbot (Jiménez-Barreto et al., 2021), and higher acceptance of in-vehicle gesture interaction with an automotive user interface (Stiegemeier et al., 2022).

Furthermore, a review of 110 CHI and CHI PLAY papers confirmed the growing interest from online game design and player experience studies in the SDT and the theoretical concepts of intrinsic motivation and need satisfaction (Tyack & Mekler, 2020). In the domain of gamification, Sailer et al. (2017) indicated that specific online game design factors would be able to support users' BPN Satisfaction and subsequently motivation.

Specifically, the needs for Competence and Autonomy were satisfied more strongly by leaderboard and performance graphs while Relatedness was supported by avatars and teammates. A study by Reer et al. (2022) showed that Virtual Reality (VR) had a positive impact on users' Competence and Autonomy Need Satisfaction as well as game enjoyment, in comparison to the same game without VR.

For user experience design, BPN Satisfaction has proven to have a positive influence on users' experience when interacting with technologies. Pioneering the idea of involving psychological need assessment in user experience, Hassenzahl et al. (2010) analyzed over 500 positive experiences with interactive technologies while assessing user's fulfillment of 10 psychological needs based on Sheldon et al. (2001). The results revealed that specifically the fulfillment of the Competence and Relatedness Need, amongst other factors such as stimulation and popularity, are key drivers for positive affect in technology interaction.

Multiple user experience studies have followed this approach and assessed the importance of Sheldon's psychological needs for user experience and technology design (see e.g., Frison et al., 2019; Karapanos et al., 2015; Lallemand et al., 2014; Partala & Kallinen, 2012; Tuch et al., 2013). Interestingly, the original study by Sheldon et al. (2001) pointed out that the needs for autonomy, competence, and relatedness (in line with the SDT) were always amongst the top four needs when determining the most fundamental needs for humans across three studies. In support of this, the METUX (Motivation, Engagement, and Thriving in User Experience) model was formed to provide a framework for designers and developers to consider BPN Satisfaction at six different stages, or *spheres*, of technology use and interaction (technology adoption, interface interaction, technology enabled task, technology supported behavior, life impact, and societal impact; Peters et al., 2018).

Integrating the BPN in design practices would benefit both, the developers, as BPN Satisfaction fosters user engagement, as well as the users, due to the positive effects on their well-being.

Moreover, several ethical guidelines and frameworks were formed over the recent years (see e.g., Chatila et al., 2017; Ikonen et al., 2009; Jones et al., 2014) to establish principles for the development of autonomous systems, highlighting the importance of human autonomy and user well-being. For example, the Association for Computing Machinery has established the following point as their first principle of ethical conduct: "Contribute to society and to human well-being, acknowledging that all people are stakeholders in computing", pointing toward the importance of considering user well-being in the processes of computing (Gotterbarn et al., 2018). Since, according to SDT and BPNT, users' well-being is the outcome of BPN Satisfaction, their integration in technology design would facilitate the conformity with ethical standards.

Considering the results from the studies outlined above, the relevance of BPN Satisfaction for user engagement and well-being is evident. Therefore, it is important that BPN Satisfaction is taken into consideration in future human–computer interaction (HCI) studies and design processes for new technologies. For example, Peters and Calvo (2021) have created guidelines to integrate BPN Satisfaction in user experience design practices with a focus on factors that support users' well-being. However, to integrate BPN Satisfaction in technology design and HCI research, appropriate and validated measures, for BPN Satisfaction in the technology context, are needed.

Measurement of Basic Psychological Need Satisfaction

BPN Satisfaction has to date been measured with various tools, such as the Basic Psychological Need Satisfaction and Frustration Scale (BPNSFS; B. Chen et al., 2015), the Balanced Measure of Psychological Needs (BMPNs; Sheldon & Hilpert, 2012), and the Basic Psychological Need Satisfaction Scale (BPNS; Ilardi et al., 1993). Further, a variety of scales were adapted to specific contexts, such as the Basic Psychological Needs in Exercise Scale (Vlachopoulos et al., 2010), the Basic Psychological Needs at School Scale (Tian, Han, & Huebner, 2014), and the Basic Psychological Needs at Work Scale (Brien et al., 2012).

However, there is no specific BPN scale tailored to technology use. Previous studies assessing BPN Satisfaction in broader user experience design contexts (e.g., Hassenzahl et al., 2010; Karapanos et al., 2015; Lallemand et al., 2014; Partala & Kallinen, 2012; Tuch et al., 2013), automotive user interface design (Stiegemeier et al., 2022), or during chatbot interaction (e.g., De Vreede et al., 2021; Jiménez-Barreto et al., 2021; Moradbakhti et al., 2022) have used individually adapted versions of the existing scales to measure BPN Satisfaction. Even though the studies have confirmed the significance and influence of BPN Satisfaction for HCI research, the inconsistent use of measures is problematic in terms of comparability between studies and their replicability. As suggested by Scheel et al. (2021), studies should refrain from prematurely testing hypotheses before having developed sound measurements. Moreover, hypotheses can only be measured if the construct of interest is accurately applied in the study. If a study fails to apply a valid measure, theoretical inferences cannot be made as the findings could equally measure random noise or a related but nevertheless distinct construct (Scheel et al., 2021). Specifically, in HCI and user experience studies, scale development procedures are not commonly used (Bargas-Avila & Hornbæk, 2011) which highlights the necessity to introduce the benefits of applying validated scales to the HCI research community [see, for example, a recent discussion in the human–robot interaction community (Leichtmann et al., 2022)].

The Present Study

The present study aimed to develop a scale that demonstrates good construct validity for measuring BPNS in the context of technology use: The Basic Psychological Need Satisfaction in Technology Use Scale (BPN-TU scale). Since no proper BPN scale that is adapted to the technology context has to date been rigorously developed and validated, studies have used individually adapted versions of existing BPN scales (e.g., B. Chen et al., 2015; Moradbakhti et al., 2022; Sheldon & Hilpert, 2012), thereby impeding comparability of results across studies. Our contribution will allow HCI researchers to use a solid scale that has undergone construct, discriminant, and predictive validation across contexts and technologies, both simplifying and strengthening current methods of assessing BPN Satisfaction in technology use.

Further, to date, no study has addressed the potential two-fold nature of the Need for Relatedness in technology use, proper exploration of which is impossible with existing BPN scales. The current scale was furthermore designed in a way that it can be used widely in future studies addressing BPN in the context of a variety of different technologies as it is not limited to a specific application. We chose four technologies to prove the applicability of the scale to different contexts and technologies. We conducted the first study with an AI Voice Assistant in a banking context and a second study with an AI Voice Assistant in a virtual reality game. To focus on the Relatedness to Others Need, we ran a

Table 1. Study overview

Study	Technology	Sample size	Main focus of study
Interviews	N/A	10	Item generation
Study 1	Chatbot	355	Model fit comparison
Study 2	Exoskeleton	120	Confirmatory factor analysis
Study 3	Voice assistant	124	Confirmatory factor analysis
Study 4	Care robot	222	English translation

study with an exoskeleton (noninteractive technology) simulating factory work. Even though participants worked alone, they were asked to imagine themselves as being someone working with others in a factory either being the only one wearing an exoskeleton or being one of many wearing an exoskeleton. Lastly, we conducted a study with an assistive robot for in-home rehabilitation. Taken together, we believe that we cover diverse fields of application and technologies and highly encourage other studies to expand on the current examples.

To ensure construct validity, we conducted four separate studies and analyzed the structure of the BPN-TU scale using confirmatory factor analyses (CFA), to test if the theoretical constructs according to the BPN theory are reflected (see Table 1). Invariance testing (with Studies 1 to 3) in a final step, after confirming the construct structure in each study separately, will allow to test if in fact the same construct is being measured across different technologies. In Study 4, the English version of the scale will be evaluated, and additional invariance testing between Study 1 and Study 4 will confirm if the construct structure fits the German and English versions of the scale. Furthermore, we run correlation analyses with the BPN items and other existing constructs, to assess the discriminant and convergent validity of the new BPN-TU scale (Study 1) for which the BPN scale should be different or similar according to theory. Lastly, we also measure the predictive validity of the BPN scale by testing its relationship with the intention to use the technologies in Studies 1 and 4.

Methods

Development and evaluation of the Basic Psychological Need Satisfaction for Technology Use Scale (BPN-TU) comprised five separate steps (see Table 1). To ensure sound methodology, we followed best practice guidelines for the scale development (see e.g., Boateng et al., 2018; Cronbach & Meehl, 1955) which typically include steps of item generation, scale construction, and scale evaluation.

We report how we determined our sample size, all data exclusions (if any), all data inclusion/exclusion criteria, whether inclusion/exclusion criteria were established prior to data analysis, all measures in the study, and all analyses including all tested models. If we use inferential tests, we report exact *p*-values, effect sizes, and 95% confidence or credible intervals.

Item Generation

First, a pool of 85 items in German was created based on existing BPN scales (German adaptation of the BPNSFS by Heissel at al., 2019; Sheldon & Hilpert, 2012) and additional items that were expected to fit the technology context (e.g. “When I use _, I feel like my social circle reacts positively to my use of _;” “I can imagine building a bond with _;” or “When I use _, I feel like the interaction goes both ways.”). Since some items were very similar to each other and only phrased differently, we markedly reduced the overall item number. Considering both aspects of the Need for Relatedness in the technology context, we created items for four need categories: Autonomy Need, Competence Need, Need for Relatedness to Others, Need for Relatedness to Technology.

These items were evaluated in individual interviews with five experts using the thinking-aloud method (Ericsson & Simon, 1993). The interviews lasted an hour each and were conducted via Zoom. All experts had a strong background in human–machine interaction, and collectively they had experience of a wide range of technologies. In each interview, the interviewer went through the potential items step by step while the experts openly discussed their thoughts, concerns, and preferences. Some experts also proposed additional items. Based on all five expert opinions, the item pool was further modified and reduced. The chosen items were items for which the majority of experts expressed a preference, e.g., they thought of it as a useful addition to measure the construct. Finally, the items were also evaluated by five lay people (no background in human–technology interaction research and no tertiary education) via the thinking-aloud method to ensure understandability of the items to a wider audience. The interviews lasted between 30 min and 1 h and were conducted in person or via Zoom. Based on these 10 interviews, the original item pool was reviewed by the authors, adapted, and reduced to 24 items.

Study 1: BPN Satisfaction for the Interaction With a Banking Bot

The purpose of Study 1 was to provide initial construct validation of the 4 × 6 factor model (4 factors for the four BPN with six indicators each) according to the BPN theory and to test alternative models to find the best-fitting model. The technology used for this study was a *Banking Bot*, a chatbot for everyday banking activities. In addition to the need scale, we also included variables from existing models (e.g., the unified theory of acceptance and use of technology [UTAUT]; Venkatesh et al., 2003) to examine correlations between the constructs. The correlations can provide information on whether the measured constructs of the new scale are different or similar to other constructs used in HCI research (discriminant and convergent validity). In addition, we can assess if the BPN constructs can predict relevant outcomes of HCI (predictive validity).

The chosen constructs are relevant and often referred to in HCI literature, such as anthropomorphism (see e.g., Epley et al., 2007; Eyssel et al., 2011, 2012) which based on theory, can be linked to the Relatedness to Technology Need, since both constructs assume the human tendency to ascribe human-like characteristics to nonhuman entities; as well as the UTAUT (see e.g., Attuquayefio & Addo, 2014; Venkatesh et al., 2003) which has previously been linked to the SDT and BPN Satisfaction (see e.g., Alowayr & Al-Azawei, 2021; Hsieh, 2023; Hsu, 2023; Osei et al., 2022). Specifically, we were interested in including the UTAUT factors Social Influence and Performance Expectancy, as we see a theoretical link between Social Influence and Relatedness to Others, as well as Performance Expectancy and the Needs for Autonomy and Competence. Similarly, we chose to include measures of Warmth and Competence, as we expect a relationship between Relatedness and Warmth perceptions, as well as Competence perception of the technology and users own Competence Satisfaction (Bergmann et al., 2012). We included Perceived Behavioural Control as it was previously linked to users' autonomy perceptions (see e.g., Shen et al., 2022), particularly in the context of autonomous driving (Rödel et al., 2014). Lastly, Self-Identity has previously been linked to social identity and self-concepts in relation to technology (K. T. Cheng & Guo, 2015), so called "IT identity" (Carter and Grover, 2015), as well as autonomy (Wiklund-Engblom et al., 2009). We therefore expect Self-Identity to be linked to the Relatedness Needs and Autonomy.

Participants

Three hundred twenty-two Austrian participants were recruited via the online panel provider *Respondi*. 33 additional participants were recruited from university courses (in Psychology and Computer Science), via internal university staff and student newsletters, and our lab's Facebook page. The final sample consisted of $N = 355$ (177 women, 176 men, two nonbinary, $M_{\text{age}} = 44.18$, $\text{Range}_{\text{age}} = 16–75$, $SD_{\text{age}} = 15.19$).

Measures

- The initial Basic Psychological Need Satisfaction for Technology Use Scale (BPN-TU) was assessed with six items per need and 24 items in total. The items were rated on a five-point Likert scale from 1 = *does not apply at all* to 5 = *fully applies.* The final (shortened) English version of the BPN-TU scale can be seen below (Table 2), the final (shortened) German BPN-TU scale can be seen in Table A1 in the Appendix, and the original German 4 × 6 item scale can be found in the supplementary materials.
- UTAUT Performance Expectancy was assessed with five items based on the original model (see Venkatesh et al., 2003). An example item was: "The usage of the Banking Bot increases my effectiveness." The items were rated on a five-point Likert scale from 1 = *does not apply at all* to 5 = *fully applies.*
- UTAUT Social Influence was assessed with three items based on the original model (see Venkatesh et al., 2003). An example item was: "People that are important to me think I should use the Banking Bot". The items were rated on a five-point Likert scale from 1 = *does not apply at all* to 5 = *fully applies.*
- Perceived Behavioral Control (PBC) was assessed with three items based on the extended version (Ajzen, 1985) of the theory of reasoned action (Fishbein et al., 1975). An example item was: "It is easy for me to get the Banking Bot to do what I want." The items were rated on a five-point Likert scale from 1 = *does not apply at all* to 5 = *fully applies.*
- Self-Identity was assessed with two items based on Self-Identity items that were previously used by Lee et al. (2001, 2006). An example item was: "The use of the Banking Bot would represent my personal values." The items were rated on a five-point Likert scale from 1 = *does not apply* at all to 5 = *fully applies.*
- Warmth & Competence was assessed with three items to measure competence (e.g., "How competent did you perceive the Banking Bot?") and three items to measure warmth (e.g., "How warm hearted did you perceive the Banking Bot"). These items were based on the classic constructs of warmth and competence as established by Fiske et al. (2007) that have previously been applied in studies in the domain of human–technology interaction (Bergmann et al., 2012). The items were rated on a five-point Likert scale from 1 = *does not apply at all* to 5 = *fully applies.*

Table 2. Final English Basic Psychological Need Satisfaction for Technology Use Scale (German version in the Appendix)

Need	Item	Not at all	Not really	Neutral	Somewhat	Very much
Autonomy	When I use __, I can act independently.	1	2	3	4	5
Autonomy	When I use __, I feel like I am in control.	1	2	3	4	5
Autonomy	When I use __, I feel like I can perform actions in the way I want to.	1	2	3	4	5
Competence	When I use __, I feel competent.	1	2	3	4	5
Competence	When I use __, I feel empowered in my own abilities.	1	2	3	4	5
Competence	When I use __, I feel confident that I can reach my goals.	1	2	3	4	5
Relatedness to Others	When I use __, I feel less alone.	1	2	3	4	5
Relatedness to Others	When I use __, I feel like my social circle reacts positively to my use of __.	1	2	3	4	5
Relatedness to Others	When I use __, I feel like I look good in front of my social circle.	1	2	3	4	5
Relatedness to Technology	I can imagine building a bond with __.	1	2	3	4	5
Relatedness to Technology	I have a friendly feeling towards __.	1	2	3	4	5
Relatedness to Technology	When I use __, I feel like the interaction goes both ways.	1	2	3	4	5

- Anthropomorphism was assessed as a semantic differential based on the Godspeed scale (Bartneck et al., 2009).
- Dependent Variable: Intention to Use: Participants' intention to use the Banking Bot (see technology acceptance model [TAM]; Davis, 1989) was assessed with two items: "I could imagine to use the robot in the future" and "I would like to inform myself about products that are similar to this robot." The items were rated on a five-point Likert scale from 1 = *does not apply at all* to 5 = *fully applies*.
- Additional Variables: In addition to the variables mentioned above, participant age, gender, openness to technology, and previous experience with technology were assessed. Since these variables were not relevant to scale development, we do not elaborate on their measurement in more detail.

Procedure

This study was an online study with video vignettes of a chatbot Banking Bot for everyday banking activities (a screenshot of the chatbot can be seen in Figure 1). Participants were told that they would see a prototype which they would later evaluate.

They first provided their demographic information and were then randomly assigned to one of four video conditions. Each video followed the same style of introduction, but the text the chatbot would use in each condition to introduce its services was slightly varied to address one need specifically. For example, to address the Competence Need, the chatbot introduced its services as "I can carry out transfers at your request [...]. Even if you have complex requests, such as expense analyses, I can run professional calculations for you." The same sentence was phrased as "I can carry out transfers at your request [...]. I am also happy to refer you to my colleagues in the branch." to address the Need for Relatedness to Others. After watching the videos, participants were instructed to complete the questionnaires on BPN-TU, UTAUT Performance Expectancy, etc. Finally, participants were debriefed and redirected to *Respondi*'s platform to process their financial compensation. Participants received €0.50 as an incentive for their participation (approx. 10 min).

Results and Discussion

CFA was performed using the diagonally weighted least squares estimator (DWLS), as the variables for the need scale were originally categorical variables (Mindrila, 2010). In line with suggestions on how to treat ordinal data in factor analyses, we did code the categorical variables as continuous (Robitzsch, 2020; Savalei, 2021). Moreover, we also ran the analyses with the maximum likelihood (ML) estimator for comparison, the results of which confirmed good fit and can be found in the supplementary materials. To see the data distribution in all four studies, please see the violin plots in the Supplementary Materials.

The fit of the model was evaluated using conventional fit indices (e.g., Brown, 2015; Mair, 2018): the χ^2 goodness-of-fit statistics as well as the comparative fit index (CFI; good fit > .95), the Tucker–Lewis index (TLI; good fit > .95), the root-mean-square error of approximation (RMSEA; good fit ≤ .06), and the standardized root-mean-square residual (SRMR; good fit ≤ .08). Based on these evaluation standards, the model exhibited a good model fit (see Figure 2).

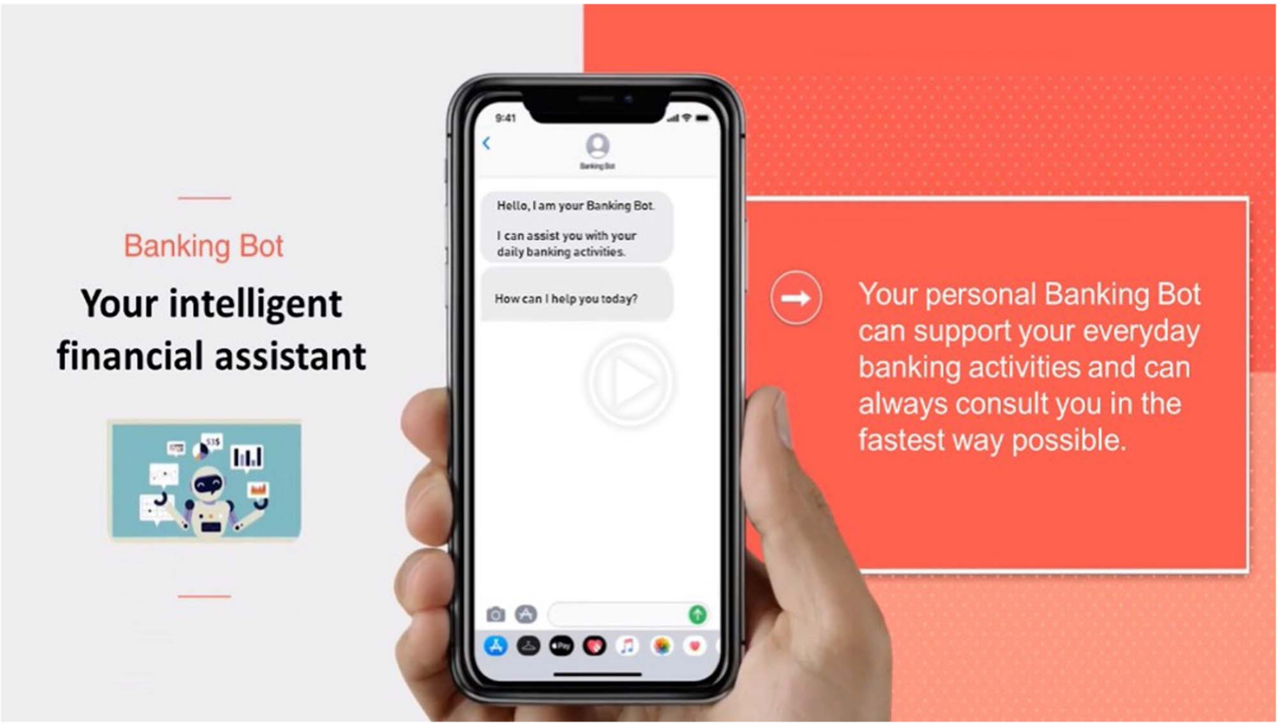

Figure 1. Screenshot from the video vignette showing the introduction of the Banking Bot. The original screenshot was translated into English.

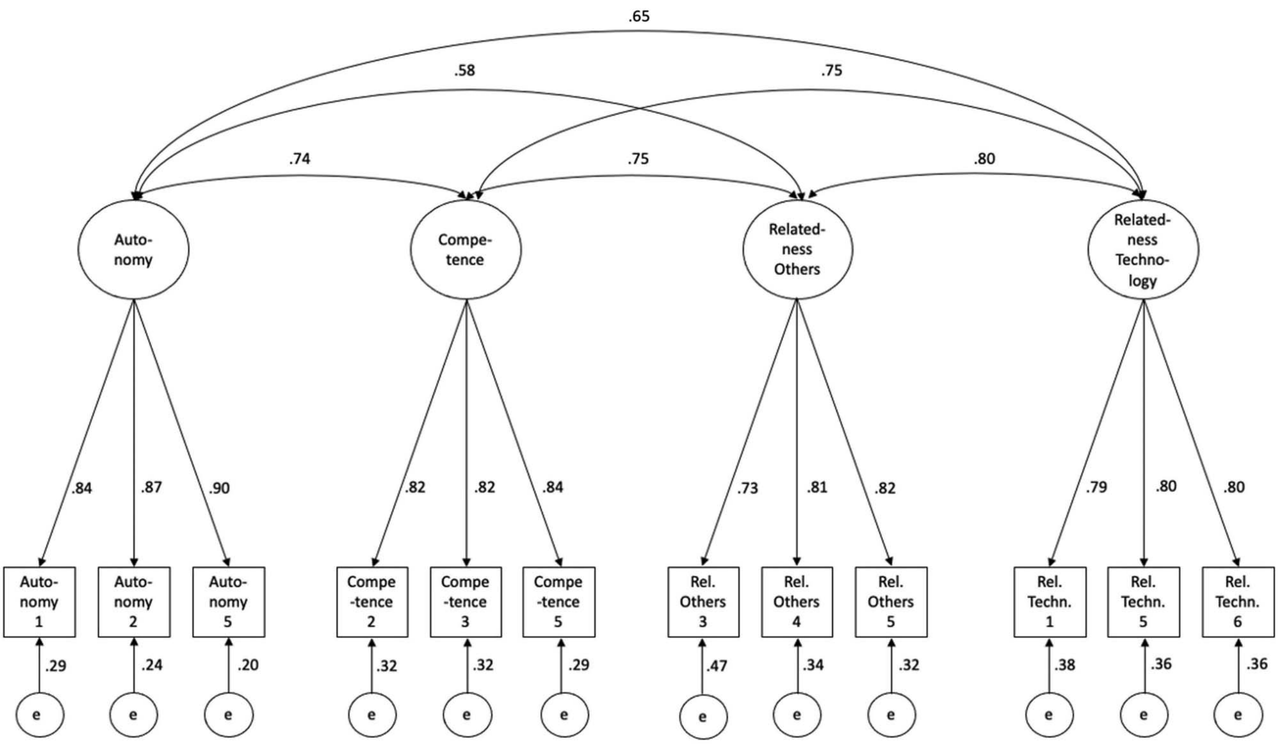

Figure 2. Confirmatory factor analysis model plot Study 1.

The 4 × 6 factor model was compared to alternative measurement models, as can be seen in Table 3. Please find CFAs for all four individual BPN factors in the supplementary materials. For reference of the item numbers, please see the supplementary materials for the initial, 24 item scale in German. Specifically, three

Table 3. Model comparisons based on CFA fit indices

Model	χ^2	*df*	CFI	TLI	RMSEA	SRMR	*p*
Model 1 (4 × 6 factors)	348.17	246	.99	.99	.03	.06	<.001
Model 2 (18 items)	83.46	129	1.00	1.01	.00	.04	1.00
Model 3 (4 × 3 factors)	25.36	48	1.00	1.01	.00	.04	1.00

reverse-coded items (Autonomy 4, Relatedness to Others 2, and Relatedness to Technology 4), *Competence 1*, and *Competence 4* did not have good factor loadings as the other items ($\lambda < .60$) and were therefore excluded.

Excluding these items, we performed another CFA and assessed the modification indices. With a cutoff of 15, we discarded one more item: *Autonomy 6*. After removal of these six items, no further items needed to be excluded based on the modification indices. This resulted in a factor model with the following items: four Autonomy items (1, 2, 3, 5); four Competence items (2, 3, 5, 6); five Relatedness to Others items (1, 3, 4, 5, 6); and five Relatedness to Technology items (1, 2, 3, 5, 6). The model resulted in a good fit (see Figure 2).

Due to the nature of HCI studies that often involve either lab-based or video-based (in online studies) interaction with a technology, lengthy questionnaires are impractical and go beyond the scope of acceptable time frames for user studies. Therefore, we sought to further reduce the item number and tested a 12-item version (see Figure 2) which resulted in a similarly good fit when compared with the other models (see Figure 2). Moreover, McDonald's ω suggests good reliability for all four BPN: Autonomy $\omega = .90$; Competence $\omega = .87$; Relatedness to Others $\omega = .84$; Relatedness to Technology $\omega = .84$.

To compare the predictive validity between the short scale (4 × 3 factor model) and long scale (4 × 6 factor model), we ran correlation analyses with the outcome measure Intention to Use. Intention to Use consists of two items that measure participants' intention to use the Banking Bot, or a similar product, in the future. The Spearman correlation between Intention to Use and the long scale was positive and significant: $rs = .746$, $n = 355$, $p < .001$. The correlation between Intention to Use and the short scale also yielded a positive significant correlation with a correlation coefficient that is only marginally smaller in comparison to the long scale: $rs = .725$, $n = 355$, $p < .001$. The long scale and short scale also positively and significantly correlated with a very high correlation coefficient: $rs = .974$, $n = 355$, $p < .001$.

M, *SD*s, and Spearman correlation coefficients between the variables are reported in Table 4, and a table on interitem correlations for Study 1 can be found in the supplementary materials. As can be seen in Table 4, the constructs had significant correlations. Firstly, we can confirm discriminant validity to the other constructs included in this study, as no correlations exceeded .85 (Brown, 2015), this means that the BPN scale measures in fact different constructs compared to scales aiming to measure other constructs because one would expect high correlation coefficients if the same constructs were being measured. In addition to this, we conducted a CFA including all 11 constructs that were included in the correlations table (Table 4) using the DWLS estimator. Based on the evaluation standards, model fit was good: $\chi^2 = 221.64$, $df = 505$, $p = 1.00$, CFI = 1.00, TLI = 1.01, RMSEA = .00,

Table 4. Discriminant validity to other constructs

Construct	*M*	*SD*	1	2	3	4	5	6	7	8	9	10	11
Autonomy	2.70	1.10	—										
Competence	2.46	0.99	.65**	—									
Relatedness to Others	1.92	0.87	.51**	.62**	—								
Relatedness to Technology	1.90	0.93	.57**	.62**	.62**	—							
Performance Expectancy	2.42	1.15	.68**	.71**	.62**	.65**	—						
Social Influence	2.09	1.01	.44**	.50**	.56**	.49**	.56**	—					
Self-Identity	2.11	1.00	.63**	.70**	.62**	.63**	.71**	.50**	—				
Behavioral Control	3.41	0.91	.59**	.55**	.44**	.49**	.61**	.37**	.51**	—			
Warmth	2.85	0.87	.60**	.57**	.47**	.53**	.52**	.43**	.52**	.50**	—		
Competence	2.83	0.86	.58**	.59**	.47**	.58**	.63**	.48**	.56**	.59**	.67**	—	
Anthropomorphism	1.67	0.78	.54**	.60**	.53**	.60**	.55**	.44**	.58**	.45**	.62**	.55**	—
Intention to Use	2.33	1.18	.64**	.68**	.53**	.57**	.78**	.52**	.70**	.54**	.56**	.58**	.51**

Note. *$p < .05$. **$p < .01$.

Table 5. Confirmatory factor analyses to demonstrate discriminant validity to other constructs

Model (BPN and comparable construct)	χ^2 (*df*)	*p*	CFI	TLI	RMSEA	SRMR
UTAUT_PE & BPN	40.12 (109)	1.000	1.00	1.01	.00	.03
UTAUT_SI & BPN	32.75 (80)	1.000	1.00	1.01	.00	.03
SELF_ID & BPN	27.41 (67)	1.000	1.00	1.01	.00	.03
BC & BPN	41.70 (80)	1.000	1.00	1.01	.00	.04
Competence & BPN	37.07 (80)	1.000	1.00	1.01	.00	.03
Warmth & BPN	59.50 (80)	.958	1.00	1.00	.00	.04
Anthropomorphism & BPN	37.03 (94)	1.000	1.00	1.01	.00	.03

SRMR = .03. In addition to this, we have also tested each construct in a separate CFA together with the four BPN Satisfaction factors. The model fit indices were all good and can be found in Table 5. This suggests that the BPN-TU factors are distinct from the other constructs confirming the assumption of discriminant validity.

However, we can see moderate-to-high correlations between all constructs. According to Meehl (1967) and Peter (1981), correlations between constructs from the same sample are highly likely, if the sample is large and reliability is given (at least to some degree). On the one hand, high correlations between theoretically related constructs were expected, as for example high correlations between the UTAUT Performance Expectancy scale and the Competence Satisfaction $rs = .71$, $n = 355$, $p < .01$, as well as the Autonomy Satisfaction $rs = .68$, $n = 355$, $p < .01$. In line with our expectations, Anthropomorphism also highly correlated with the Relatedness to Technology Satisfaction ($rs = .60$, $n = 355$, $p < .01$). On the other hand, high correlations also occurred between constructs, such as a correlation between the Self-Identity construct and the Competence Satisfaction ($rs = .70$, $n = 355$, $p < .01$), as well as Anthropomorphism and the Competence Satisfaction ($rs = .60$, $n = 355$, $p < .01$) which could be interpreted as a drawback. However, if we consider the definition of Self-Identity (see Lee et al., 2006), it can be derived that users who had their Competence Need more fulfilled after using the Banking Bot, perceived the use as more in line with their self-image. This does not necessarily need the influence of others. This would also explain why the correlation between Competence Satisfaction and Social Influence is lower ($rs = .50$, $n = 355$, $p < .01$) in comparison to Self-Identity ($rs = .70$, $n = 355$, $p < .01$). Moreover, Performance Expectancy highly correlated with both Self-Identity ($rs = .71$, $n = 355$, $p < .01$) and Competence Satisfaction ($rs = .71$, $n = 355$, $p < .01$), suggesting a definite relationship between users' Competence Need Satisfaction, their perception of Performance Expectancy and their own self-expectation related to banking (Self-Identity). To further investigate this relationship, future studies could explore whether individual differences in attitudes toward technology or technology affinity can influence the relationship between Self-Identity and Competence Need Satisfaction. Lastly, we want to point out that the Self-Identity items had to be adapted to fit the context of the study which could also affect the construct. The high correlation between Anthropomorphism and Competence Satisfaction ($rs = .60$, $n = 355$, $p < .01$) can also be explained based on previous research, such as the Robotic Social Attributes Scale (Carpinella et al., 2017) which includes warmth, competence, and discomfort as measures of the social perception of robots. Christoforakos et al. (2021) further found evidence that Perceived Competence of a conversational chatbot correlated with anthropomorphism to a similarly high amount as Perceived Warmth. To draw the link to Competence Satisfaction, existing results show (Moradbakhti et al., 2022) that Perceived Competence positively and significantly correlates with Competence Need Satisfaction, and the findings hold true for the current study ($rs = .59$, $n = 355$, $p < .01$). This would lead to the assumption that participants who perceived the Banking Bot as more competent, would not only anthropomorphize the Banking Bot more but simultaneously feel their Competence Need more fulfilled. Perceived Competence could thus be seen as a mediator between the two variables. The assumption can be supported by a similarly high correlation between Anthropomorphism and Competence Need Satisfaction ($rs = .60$, $n = 355$, $p < .01$) and Anthropomorphism and Perceived Competence ($rs = .55$, $n = 355$, $p < .01$). Overall, correlations with theoretically linked constructs confirm a certain degree of convergent validity. Discriminant validity can also be assumed to a certain degree since correlation coefficients do not exceed .85. We discuss potential explanations for the high correlations between constructs in the limitation section of this paper.

We also measured the predictive validity of the BPN Satisfaction items for the Intention to Use the Banking Bot. The Autonomy Satisfaction and Intention to Use had a correlation of $rs = .64$, $n = 355$, $p < .01$, the Competence Satisfaction and Intention to Use correlated at $rs = .68$, $n = 355$, $p < .01$, the Relatedness to Others Satisfaction and Intention to Use $rs = .53$, $n = 355$, $p < .01$, and Relatedness to Technology Satisfaction and Intention to Use $rs = .57$, $n = 355$, $p < .01$. As the correlation coefficients are all medium ranging from .53 to .68, a considerable degree of predictive power can be assumed.

The English version of 12-item scale is given in Table 2. The German version of the 12-item scale can be found in Table A1 in the Appendix.

Study 2: BPN Satisfaction for the Usage of an Exoskeleton in an Industrial Context

In Study 2, we tested whether the 4 × 3 factor model of BPN (that is four needs with three items each, see Model 3) would also be a good fit for data of the new sample using a different technology. To assess whether the scale could be applied to a wide range of different technologies, we used an active exoskeleton (active exoskeletons are used to either enhance human strength or reduce the energy consumption of the body) in Study 2. Since exoskeletons are noninteractive, the Satisfaction of the Need for Relatedness to Technology items was not included in this study. However, as exoskeletons can have influence on how workers are perceived by other coworkers, we assessed the Satisfaction of the Need for Relatedness to Others. Study 2 was part of a larger research project, and more constructs had been measured in this study, but here we only report measures that were relevant to scale development.

Participants

In total, 120 (73 men, 46 women, one nonbinary, $M_{age} = 28.43$, $\text{Range}_{age} = 18–62$, $SD_{age} = 9.20$) participants took part in the laboratory study. Participants were recruited from an elective class for Computer Science and Artificial Intelligence university students and via internal university staff and student newsletters and our lab's Facebook page.

Measures and Procedure

Study 2 was conducted in a laboratory setting on an Austrian university campus. Participants were required to complete a series of tasks wearing the exoskeleton "Ironhand" (Bioservo). The tasks included activities typical of work in industrial settings where the exoskeleton would support workers (e.g., riveting, screwing). Before starting, participants read an information sheet and were told that they would be trying out the exoskeleton for a company producing wooden kitchens and that they were to test and provide feedback on how the individual tasks could be performed with exoskeleton support. The study setup and exoskeleton can be seen in Figure 3.

Participants were randomly assigned to one of two conditions: (1) In condition one, participants were told that they should imagine themselves working alone with the exoskeleton in the company, as the company was planning to buy it for only one person due to its high cost; (2) in condition two, participants were told that the company was planning to provide all workers with this exoskeleton, so they should imagine themselves working in an environment where multiple workers would wear it. This manipulation can impact the Need for Relatedness to Others; we report group differences regarding the Need for Relatedness to Others below. Once participants had finished the tasks, they used a tablet to complete a questionnaire and were then debriefed by an instructor.

Figure 3. Exemplary picture of the experimenter executing one of the tasks while wearing the exoskeleton. Printed by permission.

Additional measures that were assessed are not included here, as they were not relevant to scale development.

Results and Discussion

An independent sample t test revealed that there were no significant group differences between condition one and two in the Need for Relatedness to Others $t(118) = -1.62$, $p = .109$.

Spearman correlation coefficients between the BPN-TU factors are reported in the supplementary materials for Study 2. CFA was performed using the DWLS method; for ML estimation, see the supplementary materials. Based on the evaluation standards, model fit was good (see Figure 4): $\chi^2 = 15.65$, $df = 24$, $p = .90$, CFI = 1.00, TLI = 1.05, RMSEA = .00, $SRMR = .06$. McDonald's ω suggests acceptable good reliability for all three BPN: Autonomy ω = .66; Competence ω = .76; Relatedness to Others ω = .60.

The factor loading for the Relatedness to Others item 3 ("When I use, I feel less alone.") is lower in comparison to the other factor loadings, and McDonald's ω is also below the desired threshold of .70. This may be the case due to the artificiality of the laboratory environment, which only to a certain extent simulates an actual workplace with

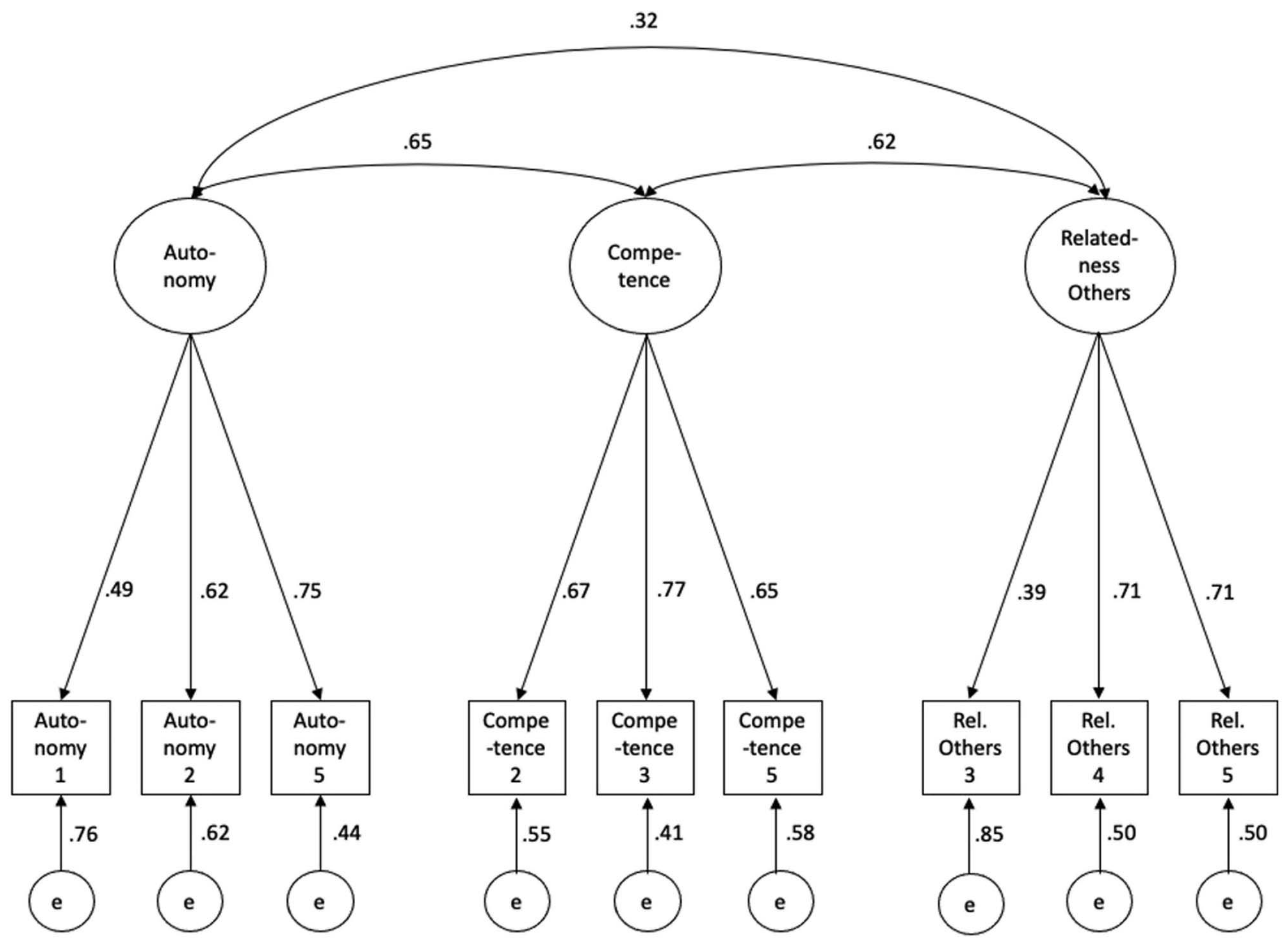

Figure 4. Confirmatory factor analysis model plot Study 2.

otherwise strong social embedding, as participants worked alone in the laboratory and were simply asked to imagine themselves working with others in the factory.

In sum, Study 2 confirmed the factor structure of the BPN-TU scale with an active exoskeleton as the technology of interest.

Study 3: BPN Satisfaction for the Interaction With an AI Voice Assistant

Study 3 was the second confirmatory study to test whether the 3 × 4 model structure would also fit the data of a new sample using a different technology, a voice assistant as a decision support. Again, tests were performed in a laboratory setting, but this time the technology encountered was an Artificial Intelligence (AI) voice assistant that participants could interact with in a Virtual Reality (VR) game environment. Concerning the Satisfaction of the Need for Relatedness, Study 2 tested only the Satisfaction of the Need for Relatedness to Others. Study 3 thus complemented Study 2 by testing only the Satisfaction of the Need for Relatedness to Technology items, with the voice assistant being expected to be perceived as the interaction partner that people feel related to. Study 3 was part of a larger research project, too, but again we only report measures that were relevant to scale development.

Participants

Overall, 124 participants took part in the study (71 men, 52 women, one nonbinary, M_{age} = 27.65, $Range_{age}$ = 16–66, SD_{age} = 9.15). Participants were recruited from various university classes for students of Artificial Intelligence, Computer Science, and Psychology and via internal university staff and student newsletters and our lab's Facebook page.

Measures and Procedure

Study 3 was a VR lab study conducted on an Austrian university campus. Participants received an information sheet and entered their demographic information on a tablet before starting the VR game. The game was based

Figure 5. Screenshot from the virtual reality game showing the subtitles from a spoken sentence by the AI Assistant. Printed by permission.

on the concept of escape games, and participants were tasked with saving the fictitious planet *Xiranda* by creating a healing serum while solving several riddles and puzzles. If needed, participants would receive help from an AI voice assistant that was not visible to them, but they could hear the voice throughout the game. An impression of the VR game environment can be seen in Figure 5. There were four different voices overall (male-synthetic; male-human-like; female-synthetic; female-human-like), and participants were randomly assigned to one of these four conditions. (note: While the manipulation of the AI voice was important in the larger project, we do not report the results of the manipulation on the BPN factors as no effects are expected, and it is not important for the scale development.) Once the game was over, participants completed questionnaires on a tablet computer (including the BPN-TU scale) and were then debriefed by an instructor.

Additional measures that were assessed are not included here, as they were not relevant to scale development.

Results and Discussion

Spearman correlation coefficients between the BPN-TU factors are reported in the supplementary materials for Study 3. CFA was performed using the DWLS estimator, and for ML estimation, see Supplementary Materials. Based on the evaluation standards, the model fit the data well (see Figure 6): $\chi^2 = 12.39$, $df = 24$, $p = .98$, CFI = 1.00,

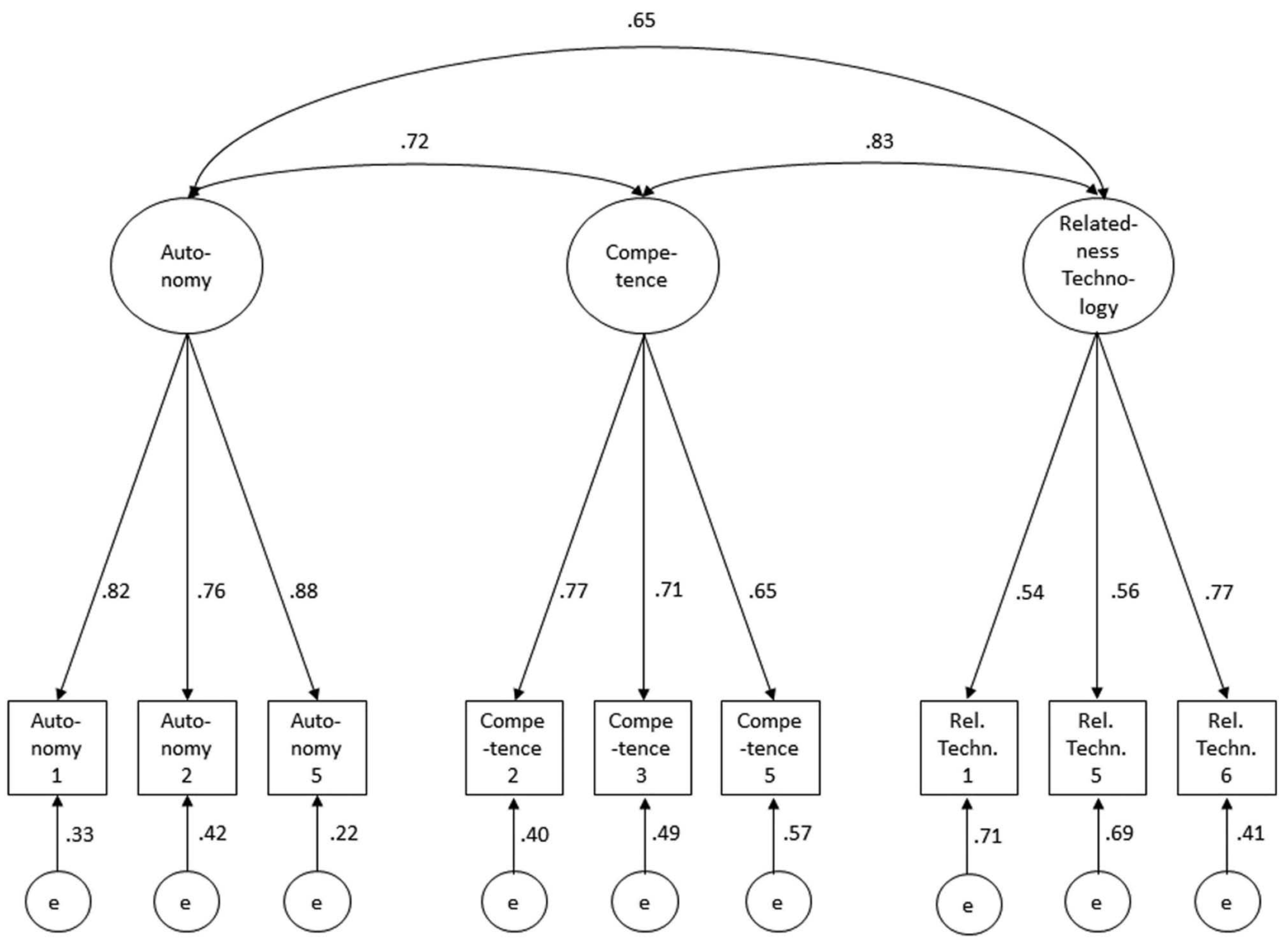

Figure 6. Confirmatory factor analysis model plot Study 3.

TLI = 1.02, RMSEA = .00, SRMR = .05. McDonald's ω suggests good reliability for Autonomy ω = .86 and Competence ω = .76 and moderate reliability for Relatedness to Technology ω = .68.

The results thus show that the new BPN-TU scale also worked in a VR setting where participants interacted with a voice assistant. This gives hints that the scale can be used with different technologies.

Invariance Testing Across Studies 1–3

The confirmatory factor models reported in the studies separately revealed good fit to the theoretical structure for different samples and different technologies including a chatbot, an exoskeleton, and a voice assistant in different settings of online, lab, and VR studies.

However, it remains unclear, if the models are comparable also in characteristics other than the general model structure. To avoid hidden invalidity, scales should also be tested for invariance across different groups (Hussey & Hughes, 2020). Thus, we tested the measurement invariance across the different technologies from Studies 1 to 3 to ensure its equivalence across technology groups. As the fit of the Relatedness Satisfaction items depends on the technology type and is thus expected to vary depending on the technology by theory, we excluded the items in our measurement invariance test. Invariance testing included the Autonomy and Competence Satisfaction items and comprised four steps: configural invariance testing (equivalence of factor structure), metric invariance testing (equivalence of factor loadings across groups), scalar invariance testing (equivalence of intercepts across groups), and strict invariance (equivalence of residual variances). The results of the four steps are shown in Table 6. To evaluate the best fitting model, the fit indices and the lowest BIC value (Bayesian Information Criterion) should be evaluated.

Results of Invariance Testing

Our results showed metric invariance and therefore also configural invariance. Thus, invariance testing confirmed that our BPN-TU scale is a good tool for measuring BPN Satisfaction across different technologies.

Study 4: English Translation of the BPN-TU Scale

While the previous studies applied the German version of the BPN-TU scale, we also tested the construct validity of an English version, to allow a wider audience to benefit from the scale. Study 4 was an online study with video vignettes of a physical rehabilitation care robot which participants were asked to evaluate (see Figure 7). The translated items were discussed with and checked by a native speaker with a background in human–computer interaction research. The scale has already been used in a study currently under review (anonymized for submission), and data will be reused here for the purpose of scale validation.

Participants

Two hundred twenty-two participants successfully completed the study (115 women, 107 men, M_{age} = 44.52, $Range_{age}$ = 18–87, SD_{age} = 15.10). Participants were recruited via the platform *Prolific* with a screening for (1) gender (men or women as this was relevant for a group comparison in the study design) and (2) long-term physical health condition and/or disability. Participants received £2.00 in compensation via Prolific's platform.

Measures and Procedure

The online study consisted of two experimental manipulations of the physical rehabilitation robot (male vs. female-gendered robot voice) which are not relevant for the current scale development.

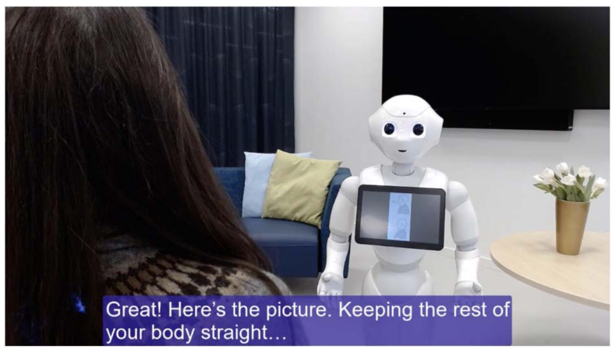

Figure 7. Screenshot from a video vignette showing the patient and the rehabilitation robot. Printed by permission.

Table 6. Results of invariance testing

Invariance	χ^2 (*df*)	*p*	CFI	TLI	RMSEA	SRMR	BIC
Configural invariance	54.47 (24)	<.001	.98	.97	.08	.03	9,370.15
Metric invariance	67.27 (32)	<.001	.98	.97	.07	.05	9,331.79
Scalar invariance	115.37 (40)	<.001	.96	.96	.10	.06	9,328.72
Strict invariance	177.93 (52)	<.001	.93	.94	.11	.07	9,314.54

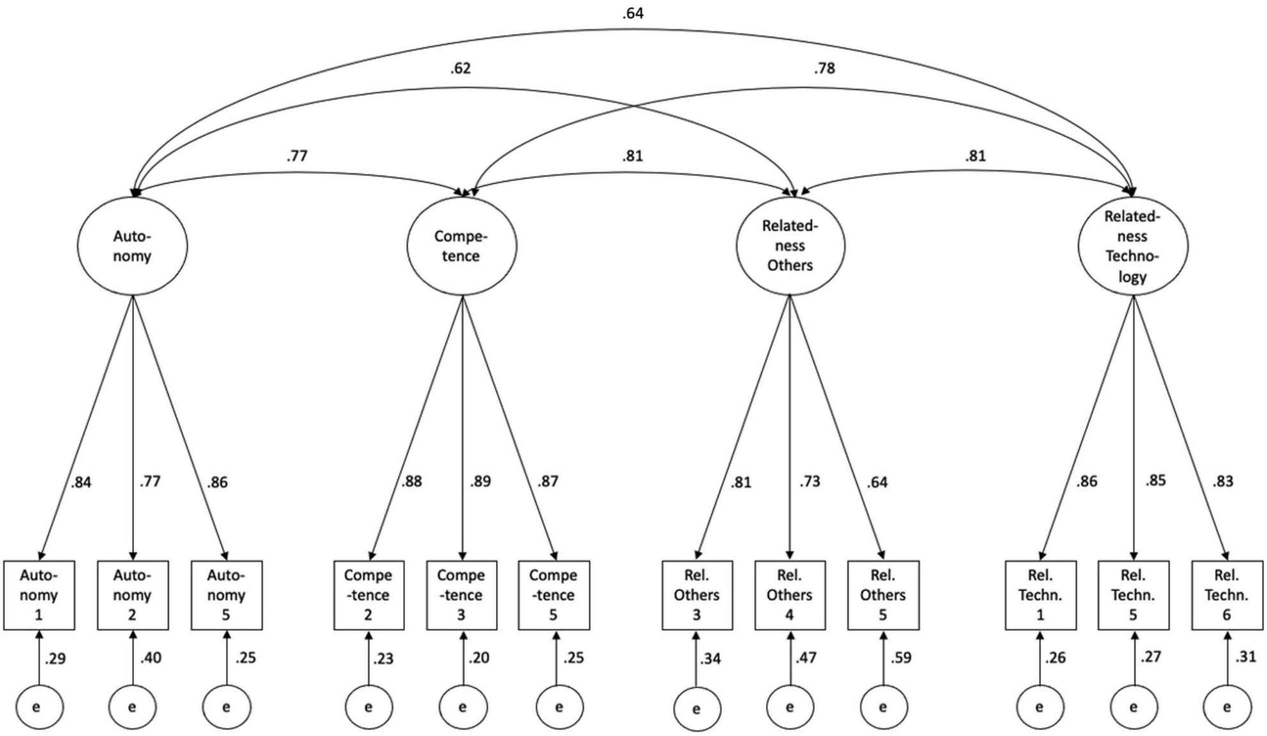

Figure 8. Confirmatory factor analysis model plot Study 4.

Additional measures that were assessed are not included here, as they were not relevant to scale development.

Results and Discussion

CFA was performed using the DWLS estimator, and for ML estimation, see supplementary materials. Based on the evaluation standards, the model of the English version of the BPN-TU scale exhibited a good model fit (see Figure 8): $\chi^2 = 22.34$, $df = 48$, $p = .99$, CFI = 1.00, TLI = 1.01, RMSEA = .00, SRMR = .04.

The full English scale can be found in Table 2 McDonald's ω suggests good reliability for all four BPN factors: Autonomy ω = .87; Competence ω = .91; Relatedness to Others ω = .78; Relatedness to Technology ω = .88. Spearman correlation coefficients between the BPN-TU factors are reported in the supplementary materials for Study 4. This shows that the scale also works well in English language in terms of construct validity.

In addition to this, participants' intention to use the care robot was assessed in Study 4, to examine the predictive validity of the scale (when applied for a different technology and context as compared to Study 1). Spearman correlation coefficients revealed high significant correlations between the Autonomy Satisfaction and Intention to Use the robot ($rs = .57$, $p < .01$, $M = 3.66$, $SD = 0.99$), the Competence Satisfaction and Intention to Use ($rs = .73$, $p < .01$, $M = 2.93$, $SD = 0.97$), the Relatedness to Others Satisfaction and Intention to Use ($rs = .59$, $p < .01$, $M = 3.26$, $SD = 1.13$), and the Relatedness to Technology Satisfaction and Intention to Use ($rs = .70$, $p < .01$, $M = 3.60$, $SD = 1.18$). Generally medium-to-high correlation coefficients between the need satisfaction and the participants' intentions to use the robot as a relevant outcome variable indicate good predictive power of the scale (similar to Study 1).

Invariance Testing Between the German and English Scales

We tested the measurement invariance across the German (Study 1) and English (Study 4) scale, to ensure its equivalence across the two languages. Invariance testing included all four BPN Satisfaction factors and comprised four steps: configural invariance testing (equivalence of factor structure), metric invariance testing (equivalence of factor loadings across groups), scalar invariance testing (equivalence of intercepts across groups), and strict invariance (equivalence of residual variances). The results of the four steps are shown in Table 7. To evaluate the best fitting model, the fit indices and the lowest BIC value should be evaluated.

Results of Invariance Testing Between the German and English Scale

Our results showed metric invariance and therefore also configural invariance for the comparison between the German and English version of the BPN-TU scale.

Table 7. Results of invariance testing between the German and English scale

Invariance	χ^2 (*df*)	*p*	CFI	TLI	RMSEA	SRMR	BIC
Configural invariance	250.21 (96)	<.001	.97	.95	.08	.04	17,143.57
Metric invariance	275.31 (104)	<.001	.96	.95	.08	.06	17,117.80
Scalar invariance	436.07 (112)	<.001	.93	.92	.10	.08	17,227.69
Strict invariance	500.22 (124)	<.001	.92	.91	.10	.09	17,037.78

General Discussion

In this article, we presented the profound development and extensive construct validation of a new scale to measure the Basic Psychological Need Satisfaction in the context of human–technology interaction (the BPN-TU scale) with empirical data from four different studies. The scale evaluation confirmed a good model fit for the 3 × 4 factor model including the needs for Autonomy, Competence, and Relatedness.

Moreover, the current study introduced the concept of distinguishing between two types of Need for Relatedness with regard to technology interaction, namely Relatedness to Others with the technology serving as a potential mediator of interpersonal relations (e.g., when the technology of interest is an exoskeleton, see Study 2) and Relatedness to Technology itself (e.g., when the technology of interest is an interactive AI-based voice assistant, see Study 3).

As can be seen from confirmatory factor analyses, a four-factor structure revealed a good fit to the data across all four studies and – depending on the interactivity of the technology– one of the needs for relatedness factors can be removed if inapplicable to the context or technology. As confirmed by invariance testing for the Autonomy and Competence Need Satisfaction, the BPN-TU scale is applicable to a variety of technologies and contexts. The current scale can thus be applied to different technologies without modification of the items, other than adding the technology to be researched in the blank fields (see Table 2), supporting the replicability of findings and comparability of results between studies. These steps confirm the construct validity of the scale.

In addition to this, correlative analyses with other constructs in Study 1 showed that the scale can also be rated positively in terms of discriminant and convergent validity. Our analyses revealed that the BPN-TU scale is linked to existing constructs in current use in technology contexts to assess user sentiments toward technological devices, such as the UTAUT Performance Expectancy scale (see Table 4) showing some degree of convergent validity. Yet, we were able to provide evidence that the BPN-TU items can be distinguished from the other scales indicated by moderately, but not perfect correlation coefficients, as well as by a model test including other constructs modeled as separate factors showing good model fit (see Study 1). However, it needs to be mentioned that we also found moderate-to-high correlations with the BPN-TU factors to factors we did not expect to have a significant relationship. This does not necessarily need to mean that this reduces the validity of one of the scales as such correlations could also be attributed to (1) common method bias (Study 1 was an online study and all questionnaires were answered one after another), (2) the so called *crud factor*, that is everything correlates to some degree with everything in the social sciences as pointed out by Meehl (1990). However, we have to acknowledge that these correlations are a limitation of this work and need to be further tested in the future.

Lastly, the predictive validity analysis confirmed that our BPN-TU scale was able to predict participants' Intention to Use different technologies in Studies 1 and 4. The scales can thus be used to derive practical implications of need satisfaction in human–technology interaction studies.

Limitations

Although we showed construct validity, convergent and discriminant validity, as well as predictive validity to some degree, we have to discuss limitations of this work.

First, as mentioned before, we also found high correlations between constructs, which we would not have expected. However, since these can also be both theoretically explained as well as by other causes such as common method bias or crud factor, the discriminant and convergent validity must be further tested in future studies. This includes a replication of the correlative results reported in Study 1 but should also include other constructs such as personality constructs (e.g., neuroticism) or other technology-related constructs (e.g., affinity for technology).

Second, even though we tested the scale with four different technologies (chatbot, exoskeleton, voice assistant, and care robot), we highly encourage other researchers to use the BPN-TU scale in their studies with additional technologies to provide further evidence for the model fit. This may include nonhumanoid robots such as manufacturing robots, different AI-based assistants, or augmented reality glasses.

Third, outcome variables other than the users' intention to use a technology could be examined to test predictive validity. For example, measures of users' motivation to use the technology, as well as users' well-being are important outcome variables that should be considered in future studies. In addition, measures that assess the influence of BPN Satisfaction on the duration and frequency of actual use in the field should be included in future research in the field.

Fourth, while we assumed construct validity by demonstrating good fit of the theoretical factor structure to the data, validity needs also be quantified by demonstrating high correlations of different measures of the same construct. As proposed by Schimmack (2021), this requires three independent measures of the same construct in a multimethod study. However, this is costly and difficult, especially in the case of BPN in context of human–technology interaction as to date not many measures exist that can be used for such a rigorous test.

As Cronbach (1971) notes, construct validation is an ever extending and thus never-ending process. This article describes a successful start of such a validation process, of which there are still far too few in the literature on HCI (Leichtmann et al., 2022, 2023). It is thus a first step toward achieving more reliable measurements and thus more robust results in user studies. Nevertheless, the validity of the BPN-TU scale still needs to be considered and tested, which is why we encourage researchers to consider this scale in the context of other constructs and technologies, as well as to discuss it on a theoretical level.

Conclusion

The main goal of this paper was to develop and evaluate a scale to measure BPN Satisfaction for contexts of technology use and interaction. As demonstrated, we were able to demonstrate construct, discriminant, and predictive validity of a scale that is applicable across different technologies and contexts. This scale validation facilitates processes of replicability and comparability across studies and disciplines. The scale can be applied in empirical research in the areas of HCI, Engineering Psychology, User Experience research, and related fields. Therefore, we encourage other researchers in the field of HCI to use this scale and include BPN Satisfaction as a measure for users' long-term well-being and as a predictor for their intention to use technologies.

References

Ajzen, I. (1985). From intentions to actions: A theory of planned behavior. In J. Kuhl, & J. Beckmann, (Eds.), *Action control: From cognition to behavior* (pp. 11–39). Springer-Verlag. https://doi.org/10.1007/978-3-642-69746-3_2

Alowayr, A., & Al-Azawei, A. (2021). Predicting mobile learning acceptance: An integrated model and empirical study based on higher education students' perceptions. *Australasian Journal of Educational Technology*, *37*(3), 38–55. https://doi.org/10.14742/ajet.6154

Attuquayefio, S., & Addo, H. (2014). Review of studies with UTAUT as conceptual framework. *European Scientific Journal*, *10*(8), 1857–7881.

Balaguer, I., González, L., Fabra, P., Castillo, I., Mercé, J., & Duda, J. L. (2012). Coaches' interpersonal style, basic psychological needs and the well- and ill-being of young soccer players: A longitudinal analysis. *Journal of Sports Sciences*, *30*(15), 1619–1629. https://doi.org/10.1080/02640414.2012.731517

Bargas-Avila, J. A., & Hornbæk, K. (2011). Old wine in new bottles or novel challenges: A critical analysis of empirical studies of user experience. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (pp. 2689–2698).

Bartneck, C., Kulić, D., Croft, E., & Zoghbi, S. (2009). Measurement instruments for the anthropomorphism, animacy, likeability, perceived intelligence, and perceived safety of robots. *International Journal of Social Robotics*, *1*, 71–81. https://doi.org/10.1007/s12369-008-0001-3

Bergmann, K., Eyssel, F., & Kopp, S. (2012). A second chance to make a first impression? How appearance and nonverbal behavior affect perceived warmth and competence of virtual agents over time. In D. Traum, W. Swartout, P. Khooshabeh, S. Kopp, S. Scherer, & A. Leuski (Eds.), *Intelligent virtual agents: 12th International Conference, IVA 2012, Santa Cruz, CA, USA, September, 12–14, 2012 – Proceedings* (pp. 126–138). Springer.

Boateng, G. O., Neilands, T. B., Frongillo, E. A., Melgar-Quiñonez, H. R., & Young, S. L. (2018). Best practices for developing and validating scales for health, social, and behavioral research: A primer. *Frontiers in Public Health*, *6*, Article 149. https://doi.org/10.3389/fpubh.2018.00149

Brien, M., Forest, J., Mageau, G. A., Boudrias, J. S., Desrumaux, P., Brunet, L., & Morin, E. M. (2012). The basic psychological needs at work scale: Measurement invariance between Canada and France. *Applied Psychology: Health and Well-Being*, *4*(2), 167–187. https://doi.org/10.1111/j.1758-0854.2012.01067.x

Brown, T. A. (2015). *Confirmatory factor analysis for applied research*. Guilford Publications.

Carpinella, C. M., Wyman, A. B., Perez, M. A., & Stroessner, S. J. (2017, March). The robotic social attributes scale (RoSAS): Development and validation. *Proceedings of the 2017 ACM/IEEE International Conference on Human-Robot Interaction*. (pp. 254–262). https://doi.org/10.1145/2909824.3020208

Carter, M., & Grover, V. (2015). Me, my self, and I(T): Conceptualizing information technology identity and its implications. *MIS Quarterly*, *39*(4), 931–957. https://doi.org/10.25300/misq/2015/39.4.9

Chatila, R., Firth-Butterflied, K., Havens, J. C., & Karachalios, K. (2017). The IEEE global initiative for ethical considerations in artificial intelligence and autonomous systems [standards]. *IEEE Robotics & Automation Magazine*, *24*(1), Article 110. https://doi.org/10.1109/mra.2017.2670225

Chen, B., Vansteenkiste, M., Beyers, W., Boone, L., Deci, E. L., Van der Kaap-Deeder, V., Duriez, B., Lens, W., Matos, L., Mouratidis, A., Ryan, R. M., Sheldon, K. M., Soenens, B., Van Petegem, S., & Verstuyf, J. (2015). Basic psychological need satisfaction, need frustration, and need strength across four cultures. *Motivation and Emotion*, *39*, 216–236. https://doi.org/10.1007/s11031-014-9450-1

Chen, K. T., & Chen, H. Y. W. (2021). Manipulating music to communicate automation reliability in conditionally automated driving: A driving simulator study. *International Journal of Human-Computer Studies*, *145*, Article 102518. https://doi.org/10.1016/j.ijhcs.2020.102518

Cheng, Z. C., & Guo, T. C. (2015). The formation of social identity and self-identity based on knowledge contribution in virtual communities: An inductive route model. *Computers in Human Behavior*, *43*, 229–241. https://doi.org/10.1016/j.chb.2014.10.056

Christoforakos, L., Gallucci, A., Surmava-Groβe, T., Ullrich, D., & Diefenbach, S. (2021). Can robots earn our trust the same way humans do? A systematic exploration of competence, warmth, and anthropomorphism as determinants of trust development in HRI. *Frontiers in Robotics and AI*, *8*, Article 640444. https://doi.org/10.3389/frobt.2021.640444

Cronbach, L. J. (1971). Test validation. In R. L. Thorndike (Ed.), *Educational measurement* (2nd ed., pp. 443–507). American Council on Education.

Cronbach, L. J., & Meehl, P. E. (1955). Construct validity in psychological tests. *Psychological Bulletin*, *52*(4), 281–302. https://doi.org/10.1037/h0040957

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, *13*(3), 319–340. https://doi.org/10.2307/249008

De Vreede, T., Raghavan, M., & De Vreede, G. J. (2021). Design foundations for AI assisted decision making: A self-determination theory approach. *Proceedings of the 54th Hawaii International Conference on System Sciences* (p. 166). INSNA.

Deci, E. L., & Ryan, R. M. (1985). *Intrinsic motivation and self-determination in human behaviour*. Plenum.

Deci, E. L., & Ryan, R. M. (2000). The "what" and "why" of goal pursuits: Human needs and the self-determination of behavior. *Psychological Inquiry*, *11*(4), 227–268. https://doi.org/10.1207/s15327965pli1104_01

Deci, E. L., & Ryan, R. M. (2014). The importance of universal psychological needs for understanding motivation in the workplace. In M. Gagné (Ed.), *The Oxford handbook of work engagement, motivation, and self-determination theory* (pp. 13–32). Oxford University Press. https://doi.org/10.1093/oxfordhb/9780199794911.013.003.

Deci, E. L., Ryan, R. M., & Vansteenkiste, M. (2008). *Self-determination theory and the explanatory role of psychological needs in human well-being*. Oxford University Press.

Epley, N., Waytz, A., & Cacioppo, J. T. (2007). On seeing human: A three-factor theory of anthropomorphism. *Psychological Review*, *114*(4), 864–886. https://doi.org/10.1037/0033-295x.114.4.864

Ericsson, K., & Simon, H. (1993). *Protocol analysis: Verbal reports as data* (rev. ed.). A Bradford Book.

Eyssel, F., Kuchenbrandt, D., & Bobinger, S. (2011). Effects of anticipated human-robot interaction and predictability of robot behavior on perceptions of anthropomorphism. *Proceedings of the 6th International Conference on Human-Robot Interaction* (pp. 61–68). https://doi.org/10.1145/1957656.1957673

Eyssel, F., Kuchenbrandt, D., Bobinger, S., De Ruiter, L., & Hegel, F. (2012). "If you sound like me, you must be more human" —On the interplay of robot and user features on human-robot acceptance and anthropomorphism. *Proceedings of the Seventh Annual ACM/IEEE International Conference on Human-Robot Interaction* (pp. 125–126).

Fishbein, M., Ajzen, I., & Belief, A. (1975). *Intention and behavior: An introduction to theory and research*. Springer.

Fiske, S. T., Cuddy, A. J., & Glick, P. (2007). Universal dimensions of social cognition: Warmth and competence. *Trends in Cognitive Sciences*, *11*(2), 77–83. https://doi.org/10.1016/j.tics.2006.11.005

Frison, A. K., Wintersberger, P., Liu, T., & Riener, A. (2019). Why do you like to drive automated? A context-dependent analysis of highly automated driving to elaborate requirements for intelligent user interfaces. *Proceedings of the 24th International Conference on Intelligent User Interfaces* (pp. 528–537). ACM.

Gotterbarn, D., Brinkman, B., Flick, C., Kirkpatrick, M. S., Miller, K., Vazansky, K., & Wolf, M. J. (2018). *ACM code of ethics and professional conduct*. Association for Computing Machinery. https://ethics.acm.org/

Gunnell, K. E., Crocker, P. R., Mack, D. E., Wilson, P. M., & Zumbo, B. D. (2014). Goal contents, motivation, psychological need satisfaction, well-being and physical activity: A test of self-determination theory over 6 months. *Psychology of Sport and Exercise*, *15*(1), 19–29. https://doi.org/10.1016/j.psychsport.2013.08.005

Hassenzahl, M., Diefenbach, S., & Göritz, A. (2010). Needs, affect, and interactive products – Facets of user experience. *Interacting With Computers*, *22*(5), 353–362. https://doi.org/10.1016/j.intcom.2010.04.002

Haugeland, I. K. F., Følstad, A., Taylor, C., & Bjørkli, C. A. (2022). Understanding the user experience of customer service chatbots: An experimental study of chatbot interaction design. *International Journal of Human-Computer Studies*, *161*, Article 102788. https://doi.org/10.1016/j.ijhcs.2022.102788

Hou, Y. T. Y., & Jung, M. F. (2021). Who is the expert? Reconciling algorithm aversion and algorithm appreciation in AI-supported decision making. *Proceedings of the ACM on Human-Computer Interaction*, *5*(CSCW2), 1–25. https://doi.org/10.1145/3479864

Hsieh, P. J. (2023). The impact of motivations, health beliefs, and basic human needs on mobile self-management: An extension of the self-determination theory perspective. *Behaviour & Information Technology*, *42*(8), 1045–1063. https://doi.org/10.1080/0144929x.2022.2059007

Hsu, L. (2023). EFL learners' self-determination and acceptance of LMOOCs: The UTAUT model. *Computer Assisted Language Learning*, *36*(7), 1177–1205. https://doi.org/10.1080/09588221.2021.1976210

Hussey, I., & Hughes, S. (2020). Hidden invalidity among 15 commonly used measures in social and personality psychology. *Advances in Methods and Practices in Psychological Science*, *3*(2), 166–184. https://doi.org/10.1177/2515245919882903

Ikonen, V., Kaasinen, E., & Niemelä, M. (2009). Defining ethical guidelines for ambient intelligence applications on a mobile phone. In *Intelligent environments (Workshops)* (pp. 261–268). IOS Press.

Ilardi, B. C., Leone, D., Kasser, T., & Ryan, R. M. (1993). Employee and supervisor ratings of motivation: Main effects and discrepancies associated with job satisfaction and adjustment in a factory setting. *Journal of Applied Social Psychology*, *23*(21), 1789–1805. https://doi.org/10.1111/j.1559-1816.1993.tb01066.x

Ilies, R., Wagner, D., Wilson, K., Ceja, L., Johnson, M., DeRue, S., & Ilgen, D. (2017). Flow at work and basic psychological needs: Effects on well-being. *Applied Psychology*, *66*(1), 3–24. https://doi.org/10.1111/apps.12075

Jiménez-Barreto, J., Rubio, N., & Molinillo, S. (2021). "Find a flight for me, Oscar!" motivational customer experiences with chatbots. *International Journal of Contemporary Hospitality Management*, *33*(11), 3860–3882.

Johannes, N., Vuorre, M., & Przybylski, A. K. (2021). Video game play is positively correlated with well-being. *Royal Society Open Science*, *8*(2), Article 202049. https://doi.org/10.1098/rsos.202049

Jones, S., Hara, S., & Augusto, J. (2014). efriend: An ethical framework for intelligent environment development. *Proceedings of the 7th International Conference on Pervasive Technologies Related to Assistive Environments* (pp. 1–4). Springer.

Karapanos, E., Gouveia, R., Hassenzahl, M., & Forlizzi, J. (2015). *It's not that hard to walk more": Peoples' experiences with wearable activity trackers*. M-ITI Technical Report.

Lallemand, C., Koenig, V., & Gronier, G. (2014). How relevant is an expert evaluation of user experience based on a psychological needs-driven approach? *Proceedings of the 8th Nordic Conference on Human–Computer Interaction: Fun, Fast, Foundational* (pp. 11–20). ACM.

Lau, O., & Ki, C. W. (2021). Can consumers' gamified, personalized, and engaging experiences with VR fashion apps increase in-app purchase intention by fulfilling needs? *Fashion and Textiles*, *8*(1), Article 36. https://doi.org/10.1186/s40691-021-00270-9

Lee, Y., Lee, J., & Lee, Z. (2001). The effect of self identity and social identity on technology acceptance. *ICIS 2001 Proceedings* (*Vol. 59*). AIS Electronic Library. https://aisel.aisnet.org/icis2001/59

Lee, Y., Lee, J., & Lee, Z. (2006). Social influence on technology acceptance behavior. *SIGMIS Database 37*(2-3), 60–75. https://doi.org/10.1145/1161345.1161355

Leichtmann, B., Hartung, J., Wilhelm, O., & Nitsch, V. (2023). New short scale to measure workers' attitudes toward the implementation of cooperative robots in industrial work settings: Instrument development and exploration of attitude structure. *International Journal of Social Robotics*, *15*, 909–930.

Leichtmann, B., & Nitsch, V. (2021). Is the social desirability effect in human-robot interaction overestimated? A conceptual replication study indicates less robust effects. *International Journal of Social Robotics*, *13*, 1013–1031. https://doi.org/10.1007/s12369-020-00688-z

Leichtmann, B., Nitsch, V., & Mara, M. (2022). Crisis ahead? Why human-robot interaction user studies may have replicability problems and directions for improvement. *Frontiers in Robotics and AI*, *9*, Article 838116. https://doi.org/10.3389/frobt.2022.838116

Li, C., Wang, C. K. J., Pyun, D. Y., & Kee Y. H. (2013). Burnout and its relations with basic psychological needs and motivation among athletes: A systematic review and meta-analysis. *Psychology of Sport and Exercise*, *14*(5), 692–700. https://doi.org/10.1016/j.psychsport.2013.04.009

Mair, P. (2018). *Modern psychometrics with R*. Springer.

Meehl, P. E. (1967). Theory-testing in psychology and physics: A methodological paradox. *Philosophy of Science*, *34*(2), 103–115. https://doi.org/10.1086/288135

Meehl, P. E. (1990). Why summaries of research on psychological theories are often uninterpretable. *Psychological Reports*, *66*(1), 195–244. https://doi.org/10.2466/pr0.1990.66.1.195

Mindrila, D. (2010). Maximum likelihood (ML) and diagonally weighted least squares (DWLS) estimation procedures: A comparison of estimation bias with ordinal and multivariate non-normal data. *International Journal of Digital Society*, *1*(1), 60–66.

Moradbakhti, L., Schreibelmayr, S., & Mara, M. (2022). Do men have no need for "feminist" artificial intelligence? Agentic and gendered voice assistants in the light of basic psychological needs. *Frontiers in Psychology*, *13*, Article 855091. https://doi.org/10.3389/fpsyg.2022.855091

Moradbakhti, L., Stiglbauer, B., & Mara, M. (2023). *Predicting technology acceptance: Basic psychological needs as important determinants of intentions to use an AI assistant*. [Manuscript submitted for publication].

Nass, C., & Moon, Y. (2000). Machines and mindlessness: Social responses to computers. *Journal of Social Issues*, *56*(1), 81–103. https://doi.org/10.1111/0022-4537.00153

Osei, H. V., Kwateng, K. O., & Boateng, K. A. (2022). Integration of personality trait, motivation and utaut 2 to understand e-learning adoption in the era of COVID-19 pandemic. *Education and Information Technologies*, *27*(8), 10705–10730. https://doi.org/10.1007/s10639-022-11047-y

Partala, T., & Kallinen, A. (2012). Understanding the most satisfying and unsatisfying user experiences: Emotions, psychological needs, and context. *Interacting With Computers*, *24*(1) 25–34. https://doi.org/10.1016/j.intcom.2011.10.001

Peng, W., Lin, J. H., Pfeiffer, K. A., & Winn, B. (2012). Need satisfaction supportive game features as motivational determinants: An experimental study of a self-determination theory guided exergame. *Media Psychology*, *15*(2), 175–196. https://doi.org/10.1080/15213269.2012.673850

Peter, J. P. (1981). Construct validity: A review of basic issues and marketing practices. *Journal of Marketing Research*, *18*(2), 133–145. https://doi.org/10.1177/002224378101800201

Peters, D., & Calvo, R. (2021). Design for wellbeing–methods and strategies for supporting psychological needs in user experience. *Extended Abstracts of the 2021 CHI Conference on Human Factors in Computing Systems* (pp. 1–3). Association for Computing Machinery.

Peters, D., Calvo, R. A., & Ryan, R. M. (2018). Designing for motivation, engagement and wellbeing in digital experience. *Frontiers in Psychology*, *9*, Article 797. https://doi.org/10.3389/fpsyg.2018.00797

Peters, D. (2023). Wellbeing supportive design–research-based guidelines for supporting psychological wellbeing in user experience. *International Journal of Human–Computer Interaction*, *39*(14), 2965–2977. https://doi.org/10.1080/10447318.2022.2089812

Reer, F., Wehden, L. O., Janzik, R., Tang, W. Y., & Quandt, T. (2022). Virtual reality technology and game enjoyment: The contributions of natural mapping and need satisfaction. *Computers in Human Behavior*, *132*, Article 107242. https://doi.org/10.1016/j.chb.2022.107242

Roberts, J. A., & David, M. E. (2020). The social media party: Fear of missing out (FOMO), social media intensity, connection, and well-being. *International Journal of Human-Computer Interaction*, *36*(4), 386–392. https://doi.org/10.1080/10447318.2019.1646517

Robitzsch, A. (2020). Why ordinal variables can (almost) always be treated as continuous variables: Clarifying assumptions of robust continuous and ordinal factor analysis estimation methods. *Frontiers in Education*, *5*, Article 589965. https://doi.org/10.3389/feduc.2020.589965

Rödel, C., Stadler, S., Meschtscherjakov, A., & Tscheligi, M. (2014). Towards autonomous cars: The effect of autonomy levels on acceptance and user experience. *Proceedings of the 6th International Conference on Automotive User Interfaces and Interactive Vehicular Applications* (pp. 1–8). Association for Computing Machinery.

Ryan, R. M., & Deci, E. L. (2000a). Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being. *American Psychologist*, *55*(1), 68–78. https://doi.org/10.1037/0003-066x.55.1.68

Ryan, R. M., & Deci, E. L. (2000b). The darker and brighter sides of human existence: Basic psychological needs as a unifying concept. *Psychological Inquiry*, *11*(4), 319–338. https://doi.org/10.1207/s15327965pli1104_03

Sailer, M., Hense, J. U., Mayr, S. K., & Mandl, H. (2017). How gamification motivates: An experimental study of the effects of specific game design elements on psychological need satisfaction. *Computers in Human Behavior*, *69*, 371–380. https://doi.org/10.1016/j.chb.2016.12.033

Savalei, V. (2021). Improving fit indices in structural equation modeling with categorical data. *Multivariate Behavioral Research*, *56*(3), 390–407. https://doi.org/10.1080/00273171.2020.1717922

Scheel, A. M., Tiokhin, L., Isager, P. M., & Lakens, D. (2021). Why hypothesis testers should spend less time testing hypotheses. *Perspectives on Psychological Science*, *16*(4), 744–755. https://doi.org/10.1177/1745691620966795

Schimmack, U. (2021). The validation crisis in psychology. *Meta-Psychology*, *5*(3). https://doi.org/10.15626/mp.2019.1645

Sheldon, K. M., Elliot, A. J., Kim, Y., & Kasser, T. (2001). What is satisfying about satisfying events? Testing 10 candidate psychological needs. *Journal of Personality and Social Psychology*, *80*(2), 325–339. https://doi.org/10.1037/0022-3514.80.2.325

Sheldon, K. M., & Hilpert, J. C. (2012). The balanced measure of psychological needs (bmpn) scale: An alternative domain general measure of need satisfaction. *Motivation and Emotion*, *36*(4), 439–451. https://doi.org/10.1007/s11031-012-9279-4

Shen, P., Wan, D., & Li, J. (2022). How human–computer interaction perception affects consumer well-being in the context of online retail: From the perspective of autonomy. *Nankai Business*

Review International, *14*(1), 102–127. https://doi.org/10.1108/nbri-03-2022-0034.

Stiegemeier, D., Bringeland, S., Kraus, J., & Baumann, M. (2022). User experience of in-vehicle gesture interaction: Exploring the effect of autonomy and competence in a mock-up experiment. *Proceedings of the 14th International Conference on Automotive User Interfaces and Interactive Vehicular Applications* (pp. 285–296). https://doi.org/10.1145/3543174.3546847

Tian, L., Chen, H., & Huebner, E. S. (2014). The longitudinal relationships between basic psychological needs satisfaction at school and school-related subjective well-being in adolescents. *Social Indicators Research*, *119*(1), 353–372. https://doi.org/10.1007/s11205-013-0495-4

Tian, L., Han, M., & Huebner, E. S. (2014). Preliminary development of the adolescent students' basic psychological needs at School Scale. *Journal of Adolescence*, *37*(3), 257–267. https://doi.org/10.1016/j.adolescence.2014.01.005

Tuch, A. N., Trusell, R., & Hornbæk, K. (2013). Analyzing users' narratives to understand experience with interactive products. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (pp. 2079–2088). ACM.

Tyack, A., & Mekler, E. D. (2020). Self-determination theory in HCI games research: Current uses and open questions. *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems* (pp. 1–22). Association for Computing Machinery. https://doi.org/10.1145/3313831.3376723

van Roy, R., & Zaman, B. (2019). Unravelling the ambivalent motivational power of gamification: A basic psychological needs perspective. *International Journal of Human-Computer Studies*, *127*, 38–50. https://doi.org/10.1016/j.ijhcs.2018.04.009

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, *27*(3), 425–478. https://doi.org/10.2307/30036540.

Vlachopoulos, S. P., Ntoumanis, N., & Smith, A. L. (2010). The basic psychological needs in exercise scale: Translation and evidence for cross-cultural validity. *International Journal of Sport and Exercise Psychology*, *8*(4), 394–412. https://doi.org/10.1080/1612197x.2010.9671960

Vuorre, M., Johannes, N., Magnusson, K., & Przybylski, A. K. (2022). Time spent playing video games is unlikely to impact well-being. *Royal Society Open Science*, *9*(7), Article 220411. https://doi.org/10.1098/rsos.220411

Wang, C., Hsu, H. C. K., Bonem, E. M., Moss, J. D., Yu, S., Nelson, D. B., & Levesque-Bristol, C. (2019). Need satisfaction and need dissatisfaction: A comparative study of online and face-to-face learning contexts. *Computers in Human Behavior*, *95*, 114–125. https://doi.org/10.1016/j.chb.2019.01.034

Wiklund-Engblom, A., Hassenzahl, M., Bengs, A., & Sperring, S. (2009). What needs tell us about user experience. *IFIP Conference on Human–Computer Interaction* (pp. 666–669). Springer. https://doi.org/10.1007/978-3-642-03658-3_71

Williams, G. C., Halvari, H., Niemiec, C. P., Sørebø Ø., Olafsen, A. H., & Westbye, C. (2014). Managerial support for basic psychological needs, somatic symptom burden and work-related correlates: A self-determination theory perspective. *Work & Stress*, *28*(4), 404–419. https://doi.org/10.1080/02678373.2014.971920

Yang, C. C., Pham, T., Ariati, J., Smith, C., & Foster, M. D. (2021). Digital social multitasking (DSMT), friendship quality, and basic psychological needs satisfaction among adolescents: Perceptions as mediators. *Journal of Youth Adolescence*, *50*(12), 2456–2471. https://doi.org/10.1007/s10964-021-01442-y

Zainuddin, Z., Shujahat, M., Chu, S. K., Haruna, H., & Farida, R. (2019). The effects of gamified flipped instruction on learner performance and need satisfaction. *Information and Learning Sciences*, *120*(11/12), 789–802. https://doi.org/10.1108/ils-07-2019-0067

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Appendix

Table A1. Final German basic psychological need satisfaction for technology use scale

Need	Item	Stimme gar nicht zu	Stimme eher nicht zu	Weder noch	Stimme eher schon zu	Stimme voll zu
Autonomy	Wenn ich __ nutze, kann ich selbständig handeln.	1	2	3	4	5
Autonomy	Wenn ich __ nutze, habe ich das Gefühl, selber die Kontrolle zu haben.	1	2	3	4	5
Autonomy	Wenn ich __ nutze, habe ich das Gefühl, dass ich Handlungen so ausführen kann, wie ich es will.	1	2	3	4	5
Competence	Wenn ich __ nutze, fühle ich mich kompetent.	1	2	3	4	5
Competence	Wenn ich __ nutze, fühle ich mich in meinen eigenen Fähigkeiten gestärkt.	1	2	3	4	5
Competence	Wenn ich __ nutze, fühle ich mich sicher, meine Ziele erreichen zu können.	1	2	3	4	5
Relatedness to Others	Wenn ich __ nutze, fühle ich mich weniger allein.	1	2	3	4	5
Relatedness to Others	Wenn ich __ nutze, habe ich das Gefühl, dass mein soziales Umfeld positiv auf meine Nutzung von __ reagiert.	1	2	3	4	5
Relatedness to 0thers	Wenn ich __ nutze, habe ich das Gefühl, dass ich vor meinem sozialen Umfeld gut dastehe.	1	2	3	4	5
Relatedness to Technology	Ich kann ich mir vorstellen eine Bindung zu __ aufzubauen.	1	2	3	4	5
Relatedness to Technology	Ich empfinde ein freundschaftliches Gefühl für __.	1	2	3	4	5
Relatedness to Technology	Wenn ich __ nutze, habe ich das Gefühl, dass die Interaktion von beiden Seiten ausgeht.	1	2	3	4	5