The Subjective Technology Adaptivity Inventory (STAI): A motivational measure of technology usage in old age

Stefan T. Kamin M.Sc[a]
E: stefan.kamin@fau.de
Frieder R. Lang PhD

[a]Institute of Psychogerontology, University of Erlangen-Nuremberg, Kobergerstrasse 62, 90408 Nuremberg, Germany

S.T. Kamin, F.R. Lang. The Subjective Technology Adaptivity Inventory (STAI): A motivational measure of technology usage in old age. Gerontechnology 2013;12(1):16-25; doi:10.4017/gt.2013.12.1.008.00 Our research explores inter-individual differences related to perceived personal adaptivity in technological environments among older adults. In two separate studies, we report findings based on the Subjective Technology Adaptivity Inventory (STAI) – a measure of inter-individual differences in the motivation to use technology. The first study involved an online sample of 1,482 participants between 60 and 91 years of age (M=68.4, SD=5.7) and investigated the psychometric quality of the measurement model. The second study was based on a paper-and-pencil sample of 163 participants between 58 and 87 years of age (M=68.6, SD=6.0) and examined the predictive validity of the instrument. The results support the psychometric quality of the instrument and its ability to predict the perceived competence to use technology and the actual usage of modern technology among older adults. Practical applications of the instrument and directions for future research are discussed.

Keywords: aging, Subjective Technology Adaptivity Inventory, technology adoption

Understanding the implications and consequences of age-related differences in the adaptive use of technology are important goals in research on aging and technology[1]. In our research we explored the impact of motivational factors related to goal selection and goal pursuit on usage of technology. We present the first results of a new measure of perceived technology adaptivity in later adulthood – that is, the Subjective Technology Adaptivity Inventory (STAI). The STAI assesses the perceived personal adaptivity of technological environments related to three constructs, that is, goal engagement and the perceived utility and perceived safety of technology. We conducted two studies to investigate the psychometric properties of the STAI and its relation to behavioral and psychological outcomes of person-technology transactions.

Theoretical framework

Our approach builds on lifespan theoretical assumptions[2,3] and the Environmental Press Model by Lawton and Nahemow[4]. According to this model, person-environment fit reflects a transaction between personal competence and the demands of the individual's environment. Transactions involve behavioral and affective outcomes in a person's responses to the environment (i.e., a technical device). In gerontechnological research, the Environmental Press Model has contributed to improving the understanding of how technological environments and technology usage may enhance the quality of life in old age[1,5]. For example, use of technology will be improved when technological contexts are challenging only to the extent that an individual is still capable of handling them. However, if the demands of technological environments deviate markedly (either below or above) from a person's competence, individuals may reject technological innovations[6]. One implication is that the dynamic changes or fluctuations that occur in cognitive, psychomotor, perceptual, and psychological resources in later adulthood require a high level of adaptability on the part of a technological system[7]. However, individuals will also have simultaneously to adjust behaviorally and mentally to the technological system concerned.

We refer to perceived personal adaptivity as an individual's response to technological demands that are associated with improved competence, and with more frequent use of technology. We thus distinguish personal subjective adaptivity from the adaptibility of the technological system. In an ideal case, subjective adaptivity may correspond to technological adaptibility, but subjective adaptivity may prevail even when there is low or no technological adaptibility. Such a differentiation between subjective adaptivity and technological adaptability may contribute to improved understanding of using technology in two ways: First, technological adaptability partly builds on (an engineer's) implicit assumptions about the behavioral or mental processes required to use technology adaptively. Thus, an improved understanding of subjective adaptivity may benefit the engineering process of adaptability. Secondly, we contend that any transaction process between the individual and a technological system entails a process of intentional action in which the individual's motivational capacities are directed toward the selection and pursuit of a goal[8]. To be clear, technological adaptability is not addressed in the current research, in which we will focus on subjective technology adaptivity related to the selection and the pursuit of technology-related goals.

We discuss the person-technology transaction process in the context of three interrelated metatheoretical principles of lifespan development, that is, selection, optimization, and compensation[2,3,8]. The consideration of selection, optimization, and compensation may contribute to an improved understanding of subjective technology adaptivity in old age. Selection, optimization, and compensation refer to general developmental processes that may not be directly reflected in the person-technology transaction. Rather, we argue that the STAI focuses on motivational constructs that are embedded in each of three metaprinciples of lifespan development as follows:

(i) The principle of selection refers to the specification, identification, and delineation of goals in life. For example, selection involves decisions about the purpose for which individuals want to use a specific technology. Selection refers to Perceived Adaptive Utility (PAU) as a process of selection when using technology in everyday life. In accordance with findings that have shown that in old age decisions to use or not to use technology depend more strongly on perceived benefits rather than costs[9] we suggest that selection is related to the perceived benefits of technology usage. Perceived benefits involve criteria of adaptive lifespan development that focus on the individual's capacity to maintain agency and behavioral control over the environment[10,11]. In this line of reasoning, older adults should be more likely to invest in technology if the potential benefits support adaptive mastery in everyday life. Perceived Adaptive Utility includes beliefs about the extent to which technology supports one's purpose in life, goal pursuit, and autonomy in everyday life. We hypothesized that individuals who maintain positive beliefs about the benefits of technology would be more likely to interact with technological systems.

(ii) The principle of optimization refers to the investment of resources or the actions taken when pursuing a goal. Optimization involves decisions about how an individual can improve his or her commitment or ability to use a specific technology. Technology-Related Goal-Engagement (TGE) refers to implementing one's intentions into the use of technology. This involves investments of effort, time, or skill. For instance, a person has to learn about the functionalities of a system or may have to maintain effort in order to overcome usage obstacles. TGE is closely related to the lifespan theoretical principle of optimization and involves strategies of goal engagement that have been described in the lifespan theory of control[10,11]. Accordingly, TGE is aimed at assessing strategies of focused investment and volitional self-regulation in person-technology transactions, thus reflecting an individual's capacity to pursue and attain technology-related usage goals.

(iii) The principle of compensation pertains to the ways in which people cope with loss and burdens in everyday life. Compensation thus refers to decisions about how an individual can develop a sense of safety when dealing with technological environments. There is considerable evidence suggesting that feelings of comfort play a critical role in a person's understanding of how to use technology, for example, with regard to computer use[12,13]. For example, anxiety has been observed to be negatively related to computer use[14], computer performance[15], and the learning of computer skills[16]. Moreover, older adults have reported higher levels of computer anxiety[17]. We submit that positive feelings about the trustworthiness, safety, and security of technology reflect compensatory resources in loss avoidance. Perceived Safety of Technology (PST) refers to a sense of trustworthiness, safety, and security while using technology. Specifically, we expected that PST would contribute to improved perceived technology competence and more frequent use of technology in old age.

Although the motivational processes of goal selection and goal pursuit describe qualitatively different functions in the course of action, they are viewed as a combined process of adaptive mastery. This relates to the lifespan theoretical assumption that selection, optimization, and compensation are closely related and reciprocal processes in adaptive functioning[18]. Consequently, we expected that the three constructs of STAI would represent different facets but would go together as one general higher-order factor of Subjective Technology Adaptivity (STA) that indicates a consistent, purposeful, and self-regulated disposition of adaptive functioning in behavioral transactions with new environmental and technological demands in later adulthood.

Objective of the current studies

In our research, we explored whether subjective technology adaptivity as measured by the STAI would serve as a resource in the use of technology in later adulthood. In line with the theoretical assumptions of the Environment Press Model[4,19], we suggest that with a stronger sense of subjective adaptivity, individuals will generate greater person-technology fit and competence. We focused on two validation criteria of person-technology fit in our attempt to demonstrate the validity of the STAI: First, the self-reported actual use of technology in everyday life[17] was used as a behavioral criterion. The second criterion was Perceived Technology Competence, which is defined as one's perceived competence and general involvement with technology. Perceived Technology Competence reflects the individual perception of competence in technological environments and was used here as a psychological indicator of person-technology fit.

We conducted two studies with independent samples of older adults and different assessment methods. Study 1 incorporated a web-based questionnaire and was designed to demonstrate the psychometric quality of the STAI. We investigated three questions: First, do the latent constructs account for the covariation of the observed indicators? Second, is there a higher-order construct that accounts for the covariation of the three first-order constructs of the STAI? Third, is the established higher-order structure invariant across the participants of the two studies? Study 2 included an independently recruited paper-and-pencil sample and primarily investigated the predictive validity of the STAI. More specifically, we expected that the higher-order construct of subjective technology adaptivity would be positively associated with technology competence and technology usage above and beyond the effects of sociodemographic predictors such as age, education, gender, and marital status. In line with existing research[17,20], we expected that women and older adults would report lower usage rates and lower levels of technology competence. In addition, we expected that higher education would be positively related to both outcomes. We did not expect effects for marital status, as research on the social embeddedness of technology adoption is still scarce.

Methods

Participants and procedure

The data for Study 1 were collected with a web-based questionnaire hosted on a German online research portal[21] dedicated to age-related research issues and projects. The study was promoted by several online communities for older adults. In addition, participants were recruited via email from a registered research participant pool. The included participants were at least 60 years old and provided all information on the questionnaire. We excluded participants with multiple or invalid submissions. The final sample included 1,482 participants between 60 and 91 years of age (M=68.4, SD=5.7) with 60.5% being female. 37.5% reported having a university

Table 1. Items in the Subjective Technology Adaptivity Inventory (STAI) that were scored on a Likert scale

Item	German phrase used	English translation
PAU 1	Die Nutzung moderner Technik hilft mir wichtige Entscheidungen zu treffen.	Using modern technology helps me to make important decisions.
PAU 2	Die Nutzung moderner Technik hilft mir bei der Bewältigung des Alltags.	Using modern technology helps me to master everyday life.
PAU 3	Die Nutzung moderner Technik hilft mir mein Leben unabhängig zu führen.	Using modern technology supports my independence.
PAU 4	Die Nutzung moderner Technik hilft mir meine täglichen Aufgaben effektiver zu bewältigen.	Using modern technology helps me to be more efficient in my daily routines.
TGE 1	Ich strenge mich so lange an, bis ein neues Gerät funktioniert, wie ich es will.	I invest as much effort as I can until a device works as intended.
TGE 2	Ich übe so lange mit einem neuen Gerät, bis ich dieses optimal benutzen kann.	I practice with a new device until I can use it as intended.
TGE 3	Ich verstärke meine Anstrengungen, wenn ein neues Gerät schwieriger zu bedienen ist als erwartet.	I put in more effort when a new device is more difficult to use than expected.
TGE 4	Wenn ein neues Gerät nicht funktioniert wie ich es will, spornt mich das zu mehr Anstrengung an.	When obstacles get in my way in using a device, I invest more effort.
PST 1	Ich vertraue moderner Technik.	I trust modern technology.
PST 2	Technischen Neuerungen sehe ich mit Zuversicht entgegen.	I feel optimistic about technological innovations.
PST 3	Ich vertraue darauf, dass neue technische Innovationen hohen Sicherheitsstandards genügen.	I believe that new technology conforms to safety standards.
PST 4	Moderne Technik gibt mir ein Gefühl der Sicherheit.	Modern technology makes me feel secure.

entrance diploma (German Fachabitur or Abitur), and 43% were married.

Study 2 employed a paper-and-pencil questionnaire and included older adults who were part of an advisory board on product development at the Institute of Psychogerontology, University of Erlangen-Nuremberg. In total, 163 participants ranging from 58 to 87 years of age (M=68.6, SD=6.0) completed the questionnaire with 27% being female. 34.8% reported having a university entrance diploma (German Fachabitur or Abitur), and 83.4% were married.

Measures

Subjective Technology Adaptivity Inventory

The STAI consists of 12 items (4 per domain) to which respondents indicate agreement or disagreement on a 5-point Likert scale (1=do not agree to 5=absolutely agree). The original items and their corresponding English translations are provided (*Table 1*), as well as means, standard deviations, factor correlations, and internal consistencies of the scales for both studies (*Table 2*).

Perceived Technology Competence

Perceived Technology Competence measures competence and subjective involvement with technology and served as a psychological indicator of person-technology fit. Participants in Study 2 responded to three statement items, that is, *"Generally, I use modern technology frequently," "I am interested in technological innovations,"* and *"I consider myself competent enough to use modern technology"*. Again, participants indicated agreement or disagreement with the statements on a 5-point Likert scale (1=do not agree to 5=absolutely agree). A mean-weighted composite of all three items was generated to indicate technology competence (M=3.74, SD=0.95). Cronbach's alpha of the items was 0.86.

Technology Usage

Technology usage was assessed in Study 2 with questions about the use of six technological devices (digital camera, mobile phone, digital music player, personal computer, video game console, Internet). Participants indicated whether they owned such a device, and how frequent the respective device was used (1=never to 4=frequent). An overall sum score was generated by summing the number of owned devices that were actually used. This score served as a behavioral criterion of validity for the STAI. The score ranged from 0 to 6 (M=3.51, SD=1.36). Cronbach's alpha was 0.70.

Covariates

Controls included age in years, dichotomized gender (0=men; 1=women), educational status (0=secondary school or below; 1=university entrance diploma), and marital status (0=not married; 1=married).

Data analysis

After reporting descriptive statistics for the instrument for both studies, we report the factor structure of the STAI based on exploratory and confirmatory factor analyses. The sample from Study 1 was randomly split into two subsamples of equal size (n=741 each). This allowed us to examine the factor structure of the inventory from an EFA (Exploratory Factor Analysis) perspective and to cross-validate the measurement model within a more rigorous CFA (Confirmatory Factor Analysis) framework. EFA refers to an exploratory factor analysis in which no structure is imposed on the relation between observed indicators and latent variables, allowing cross-loadings on each factor. CFA refers to a confirmatory factor analysis with an imposed structure in which cross-loadings of divergent factors are fixed to zero. The two subsamples were then combined to conduct a full-sample second-order CFA to account for the covariation among the three first-order factors of the inventory. The first-order factors in this model represent indicators of the higher-order factor of technology adaptivity, and the regression paths represent second-order factor loadings. This model reflects our hypothesis that goal engagement, perceived usefulness, and perceived safety can be accounted for by a general factor of subjective technology adaptivity. In comparison to first-order models with correlated factors, higher-order models provide a more parsimonious solution for the covariances of first-order factors[22]. Before we investigated the predictive validity of the STAI using the sample from Study 2, it was necessary to establish measurement invariance across the web-based sample from Study 1 and the paper-and-pencil sample from Study 2. This was impor-

*Table 2. Study 1 and Study 2 factor means (M) and standard deviations (SD), with correlation matrices, and reliability statistics; TGE= Technology-related Goal-Engagement; PAU= Perceived Adaptive Utility; PST= Perceived Safety of Technology; STA= Subjective Technology Adaptivity (composite of TGE, PAU and STE); **=p<0.001*

Factor	Study 1 (n=1,482)					Study 2 (n=163)				
	M±SD	α	TGE	PAU	PST	M±SD	α	TGE	PAU	PST
TGE	4.04±0.88	0.85	-			3.65±0.91	0.87	-		
PAU	3.58±0.97	0.80	0.35**	-		3.23±0.98	0.85	0.39**	-	
PST	3.71±0.84	0.81	0.48**	0.40**	-	3.49±0.75	0.78	0.40**	0.39**	-
STA	3.78±0.70	0.86	0.78**	0.77**	0.79**	3.45±0.69	0.87	0.77**	0.90**	0.74**

tant to do to rule out the possibilities of selection and method bias. Specifically, we were interested in invariance at the levels of the factor structure and first-order loadings. We comparatively tested a series of hierarchical multiple-group second-order models following the approach suggested by Chen and colleagues[23]. First, we investigated the fit of the higher-order model for Study 2 in order to ensure the viability of the measurement model for the paper-and-pencil sample. Second, configural invariance (Model 1) was specified in which no invariance constraints were imposed on either sample. Finally, metric invariance (Model 2) was specified in which the first-order factor loadings of the STAI were constrained to be equal across the participants of Study 1 and Study 2. The evaluation of invariance relied on fit indices that are relatively robust against sample size differences. Following general rules of thumb, changes of less than 0.01 in the Comparative fit index (CFI) or 0.015 in the RMSE indicate invariance in comparison to the least restrictive model[24,25]. After establishing invariance, the sample from Study 2 was used to investigate the predictive validity of the STAI. First, bivariate correlations were computed to investigate the associations between the instrument and the dependent outcomes and covariates. Using structural equation modeling, we applied the obtained second-order model to examine the usefulness of the inventory for predicting technology usage and the perceived technology competence. Again, this model includes the higher-order factor of subjective technology adaptivity in which the first-order factors are indicators of the second-order factor. This model is combined with a structural regression model, where the higher-order factor of subjective technology adaptivity predicts the latent variable of perceived technology competence and the observed outcome of technology usage while controlling for the covariates. All latent data analyses were implemented with the latent variable modeling program Mplus 6.1[26], maximum likelihood robust estimation, and geomin oblique rotation for the EFA. Model fit indices were interpreted by the following general rules of thumb[27]. Models with a comparative fit, CFI or Tucker-Lewis index (TLI), of equal to or greater than 0.95, a standardized root mean square residual (SRMR) less than or equal to 0.08, and a root mean square error of approximation (RMSEA) less than or equal to 0.06 were considered good.

Results

Descriptive analyses

Table 2 reports basic descriptive information about the STAI for both studies. As expected, the factors of the instrument were moderately intercorrelated and strongly related to the composite of all three scales, suggesting the specification of a higher-order factor model. The internal consistencies for the subscales and the composite score were good and ranged between 0.80 to 0.86 for Study 1 and 0.78 to 0.87 for Study 2.

Factorial validity

Exploratory factor analysis was applied to the first split-sample of Study 1. The results provided three eigenvalues greater than one (4.61, 1.76, 1.41) and suggested a good fit to the data, $\chi^2_{(33)}=42.554$ ($p=0.12$); CFI=0.996; TLI=0.992; RMSEA=0.020 with 90% CI=0.000 and 0.035; SRMR=0.014, thus supporting our theoretical assumptions. Table 3 shows the loading structure of the EFA model, indicating that all items provided salient loadings on their respective factors. The obtained factor solution was fit with the second split-sample of Study 1 using confirmatory factor analysis. The model provided a good fit to the data, $\chi^2_{(66)}=2593.875$ ($p<0.001$); CFI=0.979; TLI=0.972; RMSEA=0.038 with 90% CI=0.027 and 0.048; SRMR=0.036, indicating the viability of the factor solution under the more restricted assumption of zero cross-loadings. It also shows the standardized parameter estimates of the three-factor model. All items provided salient loadings on their related factors.

Higher-order structure

Using the full sample from Study 1, we extended the previously described CFA model and specified a single second-order factor that is referred to as subjective technology adaptivity (STA). The

Table 3. Study 1 (n=1,482) standardized factor loadings for the split-sample exploratory factor analysis with Mplus, allowing all cross-loadings (EFA), and for the confirmative factor analysis fixing all cross-loadings of divergent factors to zero and allowing factors to correlate (CFA) with loadings above 0.30 in bold face; TGE= Technology-related Goal-Engagement; PAU= Perceived Adaptive Utility; PST= Perceived Safety of Technology;

Item	EFA (n=741)			CFA (n=741)		
	TGE	PST	PAU	TGE	PST	PAU
TGE 1	**0.72**	-0.03	-0.02	**0.67**		
TGE 2	**0.72**	0.07	-0.02	**0.77**		
TGE 3	**0.88**	-0.05	0.01	**0.80**		
TGE 4	**0.71**	0.06	0.04	**0.79**		
PST 1	0.00	**0.75**	0.13		**0.74**	
PST 2	0.19	**0.51**	-0.03		**0.70**	
PST 3	-0.03	**0.69**	0.04		**0.66**	
PST 4	0.01	**0.67**	0.18		**0.81**	
PAU 1	0.10	0.01	**0.53**			**0.64**
PAU 2	-0.01	-0.06	**0.71**			**0.77**
PAU 3	0.08	0.07	**0.58**			**0.74**
PAU 4	-0.02	-0.04	**0.83**			**0.77**

*Table 4. Test results of measurement invariance across Study 1 and Study 2 (n=1,645); χ2=Chi-Square value; df=Degrees of freedom; CFI=Comparative Fit Index; RMSEA=Root Mean Square Error of Approximation; *=p<0.05; **=p<0.001*

Item	χ2	df	CFI	RMSEA
Single group solutions				
Study 1 (n=1,482)	184.779**	51	0.972	0.042
Study 2 (n=163)	81.001*	51	0.953	0.060
Measurement invariance				
Configural invariance (model 1)	265.461**	102	0.971	0.043
Metric invariance (model 2)	568.454**	132	0.969	0.044

*Table 5. Correlational analysis for Study 2 (n=158); TGE= Technology-related Goal Engagement; PAU= Perceived Adaptive Utility; PST= Perceived Safety of Technology; STA= Subjective Technology Adaptivity (composite of TGE, PAU and STE); *=p<0.05; **=p<0.001*

Item	TGE	PAU	PST	STA
Age	-0.13	-0.26**	0.01	-0.18*
Gender	-0.00	-0.09	-0.17*	-0.12
Educational status	0.00	0.19*	0.08	0.13
Marital status	-0.08	-0.01	0.05	-0.02
Perceived technology competence	0.53**	0.45**	0.36**	0.59**
Technology usage	0.33**	0.40**	0.18*	0.39**

higher-order model provided an equally good fit, $\chi^2_{(51)}$=184.779 (p<0.001); CFI=0.972; TLI=0.964; RMSEA=0.042 with 90% CI=0.036 and 0.049; SRMR=0.036, and supported the higher-order conceptualization of the STAI. The standardized estimates of the first-order factors were 0.69 (TGE), 0.84 (PST), and 0.59 (PAU). The same model was established using the paper-and-pencil sample from Study 2. Compared to Study 1, the model provided a worse but still adequate fit to the data, $\chi^2_{(51)}$=81.001 (p<0.05); CFI=0.953; TLI=0.939; RMSEA=0.060 with 90% CI=0.034 and 0.084; SRMR=0.056. The standardized estimates of the first-order factors were 0.75 (TGE), 0.69 (PST), and 0.65 (PAU). After ensuring adequate fit across both samples, a multiple-group second-order model was tested to evaluate configural invariance (Model 1). The model showed a good fit (*Table 4*), $\chi^2_{(102)}$=265.461 (p<0.001); CFI=0.971; RMSEA=0.043, thus providing evidence for equal factor structures. Parameter equivalence was tested with another model that entailed the more restrictive constraint of metric invariance (Model 2). Table 4 compares the fit indices of the models with configural and metric invariance. The results showed no changes greater than 0.01 for the CFI (0.969 vs. 0.971) or the RMSEA (0.043 vs. 0.044), thus providing evidence that the web-based sample from Study 1 and the paper-and-pencil sample from Study 2 provided equal measurement of the first-order factors.

Predictive validity

Before investigating the predictive validity of the instrument by applying structural equation modeling, we computed bivariate correlations to explore the association between the STAI scales, the dependent outcomes, and the covariates in Study 2. Five participants who were missing data on the covariates were excluded from the analysis. Table 5 shows that all STAI scales were significantly related to technology competence and technology usage. The covariates showed only a few correlations. Age was negatively related to technology adaptivity and perceived adaptive utility. Additionally, being female was negatively related to perceived safety, and educational status showed a positive association with perceived adaptive utility. The results provide the first evidence of the instrument's ability to discriminate between users and nonusers of technical devices and levels of perceived technology competence.

The next step was to apply structural equation modeling to test the predictive validity of the STAI while controlling for the covariates (*Figure 1*). The model included age, gender, marital status, and educational status as covariates and estimated the direct effects of the higher-order factor of Subjective Technology Adaptivity on Perceived Technology Competence and Technology Usage. The higher-order factor is measured by the three first-order factors of the STAI, thus representing the shared variance of Technology-Related Goal-Engagement, Perceived Adaptive Utility, and Perceived Safety of Technology. Note that this model included only 158 participants due to missing data on the covariates. The results showed that the model explained a sizeable proportion of variance for Perceived Technology Competence (R^2=0.71) and Technology Usage (R^2=0.35). In terms of individual relations, technology adaptivity showed salient effects on the number of devices used (=0.40, p<0.001) and the level of perceived competence (=0.77, *p*<0.001). Moreover, usage was positively predicted by higher education (=0.20, *p*<0.001) and negatively related to increasing age (-0.27, *p*<0.001) and being female (=-0.16, *p*<0.05). Higher education (=0.13, *p*<0.05) and being female (=-0.28, *p*<0.001) were also significant predictors of perceived technology competence.

Discussion

Our research was aimed at testing the factor structure and validity of a short measure of

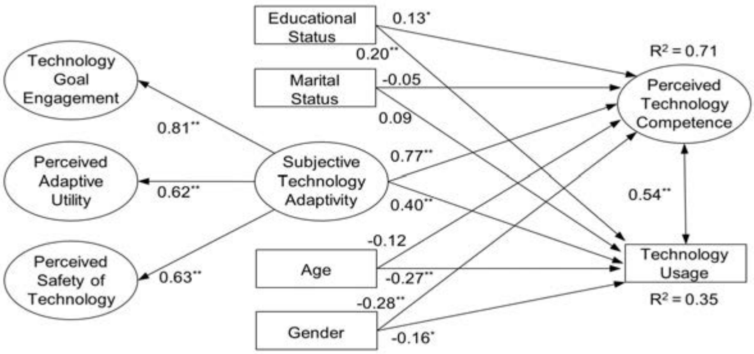

*Figure 1. Higher-order factor model of the STAI (Subjective Technology Adaptivity Inventory) predicting usage of and competence to using technology (standardized solution); R^2=coefficient of determination; n=158; $\chi 2(155)=221.784$ ($p<0.01$); Comparative fit index (CFI)=0.939; Tucker-Lewis index (TLI)=0.927; Root mean square error of approximation (RMSEA)=0.052; Standardized root mean square residual (SRMR)=0.076; *=$p<0.05$; **=$p<0.001$*

subjective technology adaptivity among older adults. The measurement model showed a clear loading structure, good fit statistics, measurement invariance, and adequate factor reliabilities. As we had expected, the three constructs of goal engagement, perceived utility, and safety formed a higher-order construct of subjective technology adaptivity that predicted technology competence among older adults. Our findings suggest that individuals who score high on the scale are more interested in technological innovations, feel more competent about dealing with technology, and are more likely to use technology as compared to those who score low on the scale. Our measure of subjective technology adaptivity allows a researcher to positively predict the number of devices used above and beyond other predictors of technology use. This suggests that goal engagement, perceived utility, and the safety of technology are important factors of behavioral competence in person-technology transactions.

Such findings contribute to the understanding of age-related differences in technology use in three ways: First, the STAI can be used as a measure of subjective technology adaptivity in order to understand the behavioral and mental competence of older target groups when they face new environmental and technological demands. This is important, for example, with regard to the design and engineering of adaptive technology. Our findings add to the existing evidence that older adults show a selective preference for adaptivity-supporting effects of technology usage in everyday life[9,28]. Thus, technology should match an individual's perception of benefits while considering potential losses and constraints on the individual's action potential. For instance, with regard to the implementation of tele-care solutions[29], it might be possible that individuals with low levels of safety and usefulness are prone to react in more adverse ways if aspects of safety and functionality are uncertain, whereas individuals who score high on the scales are more likely to cope with potential losses (for instance, data security) and find it easier to focus on the potential benefits of the system. Moreover, we suggest that usage intentions have to be translated into actual usage. Thus, adaptive technology should support focused investment and volitional self-regulation in person-technology transactions, for instance, by implementing context-dependent help and cues. This is particularly important in later life when the investment of behavioral resources becomes more challenging because of declines in sensory, motor, and cognitive functioning. Technology should adaptively respond to age-related changes over time to support the right balance between aid and self-initiated action[7]. In such a case, the STAI might be helpful for determining the appropriate level of support that does not surpass or undermine behavioral competence.

Secondly, the STAI might be important with regard to user involvement and user-centered design[30,31]. It is often difficult to select appropriate users to be included in different phases of product development[32]. For example, focus groups that involve only highly competent individuals may not represent the potential end user. Usability testing might be misleading if motivational factors moderate task performance in person-technology transactions. We suggest that user involvement would benefit from a better understanding of the motivational factors that are related to individual technology adaptivity.

Thirdly, the STAI may provide a conceptual basis for interventions that are directed at enhancing the use of technology and technology competence among older adults. This might involve the reduction of insecurity and distrust when these users are confronted with new innovations or the need to learn about the potential benefits of modern technology. Moreover, interventions could focus on problem solving or goal commitment in technological contexts and facilitate processes of goal engagement.

Our research has some limitations that ought to be considered when interpreting the findings. Our studies relied on selective subsamples of older adults in Germany. Culture and language may play a role in terms of the factor structure of the STAI. Future studies will have to demonstrate the generalizability of the STAI across different countries and cultures. Moreover, we included cross-sectional data only. Consequently, not much can be said about the extent to which the findings reflect characteristics of a specific birth cohort or whether they also imply age-associated changes and adaptation. Nothing can be said about the continuity or change of our constructs over time.

We found only moderate predictive validity with regard to technology usage. In accordance with the literature[1,17], we argue that technology usage depends on a variety of factors that go beyond the scope of this research. A promising route of future research will be to investigate motivational processes related to perceived personal adaptivity along with cognitive, physical, and contextual variables. In addition, our measure of the devices that are actually used reflects only a narrow approximation of the technological environment in which aging takes place. Thus, it may not fully capture person-technology dynamics in everyday life, for instance, with regard to the disuse of technology. In this regard, the STAI may be limited in predicting the successful implementation of new innovative technology in everyday life contexts. Clearly, further research is needed to improve the understanding of the use of innovative technology solutions. This may require observational and experimental approaches, including realistic everyday scenarios of technology use. Such methods may also allow researchers to assess possible intra-individual fluctuation in interactions with technological solutions.

Our findings shed new light on the role of perceived personal adaptivity for competent technology use. An improved understanding of psychological mechanisms of using technology in old age may result if we take a differential aging approach. For example, sociostructural and biographical factors may be relevant for an improved understanding of the motivation to use technology. Such constructs may also be associated with social structural aspects across the life course related to socioeconomic conditions, education, or other social resources (for instance, network variables). In a final step, one aim of our research was to apply a higher-order factor approach regarding subjective technology adaptivity among older adults. One implication is that not much can be said regarding the unique effects of each of three subscales on technology use. Results suggest that there are differential associations, for example, regarding stronger effects of goal engagement on technology use as compared to perceived safety. However, we contend that the higher-order factor approach allows for a broad, multifaceted assessment of motivational processes associated with subjective technology adaptivity.

Our approach of technology adaptivity differs from technology acceptance models[33] as we have embedded our work in a motivational and developmental perspective on aging. Whereas constructs of technology acceptance models are related to the characteristics of specific technological systems, the STAI focuses on models of adaptive functioning in person-technology transactions in old age that go beyond the prediction of behavioral intentions related to a specific device. We contend that our approach may contribute to an improved understanding of adaptational processes on the level of person-technology dynamics related to goal pursuit, perceptions of usefulness, and ease of use with regard to certain devices or systems. Such subjective technology adaptivity might also be related to technology-related self-efficacy beliefs[34]. Research in this domain has contributed to an improved understanding of technology use in old age[17], and we believe that the STAI might be used to investigate the conditions under which self-efficacy beliefs operate. Finally, we believe that the STAI contributes to the relatively small body of research investigating the influence of motivational factors on the technology use of older adults[9,28,35].

From the perspective of ecological gerontology, one of us has argued that individual differences in behavioral transactions with technology may also relate to successful aging outcomes and adaptive functioning across the life course[3]. Is it possible for individuals with a low level of subjective technology adaptivity to age well within a society where technology is an essential part of everyday life? Or have we overestimated the influence of technology in contextual aging? We hope that the STAI will prove its usefulness to investigate the fit between individuals and specific technological solutions, but also to address the question of adaptive functioning within the technological environments of everyday life.

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