Evaluating technology engagement in the time of COVID-19: the Technology Engagement Scale

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Abstract. Human-Computer Interaction (HCI) researchers and communication scholars have developed a broad range of theories and instruments to evaluate the concept of user engagement. However, so far, the proposed instruments are not able to fully capture the processual nature of engaging experiences with technological devices, while focusing instead on state variables or dispositional factors. Therefore, this study aimed at describing and psychometrically validating a novel instrument to measure the dynamics of the engagement with technology, namely the Technology Engagement Scale (TES). Data were collected on a representative sample of 2021 participants in Italy. Results from both the confirmatory analysis and the Rasch model suggested the mono-dimensionality of the 5-item TES. Moreover, empirical ordinal alpha indicated a very good internal consistency. Findings provide also solid evidence for the convergent validity of the proposed instrument. Finally, it emerged that TES levels were able to predict the frequency of online activities during the COVID-19 pandemic. Globally, these findings suggest that the TES could be considered a reliable and valid tool, able to evaluate the complex process of the engagement with technology in a simple, quick, and easy-to-administer manner.

1. Introduction

In recent decades, the Human-Computer Interaction (HCI) literature has emphasized the concept of user engagement as a means of describing and designing successful interactions with technology (Calvo & Peters, 2014; O'Brien & Toms, 2008, 2010; Sharafi, Hedman, & Montgomery, 2006; Triberti, Kelders, & Gaggioli, 2018; Triberti & Riva, 2015). User engagement has been studied in a variety of domains and across various technological devices (Kim, Kim, & Wachter, 2013; O'Brien & Toms, 2008), online searching (O'brien & Toms, 2013), gaming (Bouvier, Lavoué, & Sehaba, 2014; Li, Jiang, Tan, & Wei, 2014), digital health (Sutcliffe et al., 2010; Torous, Nicholas, Larsen, Firth, & Christensen, 2018), and online reading (O'Brien & Toms, 2010).

The conceptualization of user engagement as a trait, state, or process is an important distinction among the various definitions of user engagement available in the literature. (Doherty & Doherty, 2018). As a stable individual trait, Seah and Cairns (Seah & Cairns, 2008) described the engagement with video games by differentiating between cognitive absorption, namely a "propensity to become absorbed in the activities around using a computer", and immersion, namely the dynamic state of being "lost" in the game experience. More often, engagement is described as the dynamic state of the engaged user (O'Brien & Toms, 2008) or as a feature of the interaction (Davies, 2002). Jacques described six critical components of the "engaged user" in this direction: attention, motivation, perception of control, needs satisfaction, perception of time, and emotional states. (Jacques, 1996). Building upon this seminal work, O'Brien, and Toms (O'Brien & Toms, 2010) developed a model of engagement that is both a product of the interaction and a process. Their Process Model of User Engagement identified four different stages of engagement: 1) the point of engagement, 2) the period of engagement, 3) disengagement, and 4) reengagement.

In parallel with these theoretical proposals, several methodological approaches to measuring user engagement have been introduced, such as behavioral metrics (such as web clicks or time spent during an interaction with a specific device) or self-report measures evaluating the various attributes sustaining an engaging technologically mediated interaction. (O'Brien, 2016; O'brien & Toms, 2013). However, as K. Doherty and G. Doherty point out (Doherty & Doherty, 2018), while the conceptualization of engagement as a process of change is common in literature and several authors have emphasized its multifaced nature (O'Brien & Toms, 2008), it is more easily measured as a *state* variable.

The ubiquitous integration of digital solutions into our lives during the COVID-19 pandemic (Vargo, Zhu, Benwell, & Yan, 2021) necessitates a more dynamic evaluation of *technology engagement*. In the context of chronic care, where the concept of patient engagement has proven to be critical in improving treatment adherence and compliance with lifestyle changes, a useful framework for capturing the processual nature of engagement can be found (Bombard et al., 2018; Graffigna & Barello, 2018; Zullig & Bosworth, 2017). A particularly relevant model is the Patient Health Engagement Model (Graffigna & Barello, 2018; Graffigna, Barello, Bonanomi, & Lozza, 2015), which defines engagement as a "process-like and multi-dimensional experience, resulting from the conjoint cognitive (think), emotional (feel), and conative (act) enactment of individuals toward their health management a process that features four experiential positions. These various positions refer to the various relationships that individuals "build" with the healthcare system and, as a result, reflect a different mindset regarding their health conditions. In the blackout/disengagement position, individuals are psychologically and behaviorally passive in health management and delegate all care responsibilities to the healthcare system. Individuals in the arousal position are hyperactive to their health conditions and experience excessive negative feelings. Individuals in the "adhesion" position begin to accept their medical conditions, but they continue to experience anxious feelings. Individuals in the position of full commitment (i.e., eudaimonic project) become aware of their health conditions and can adopt a more optimistic outlook on life. The Patient Health Engagement Scale – PHE_® (Graffigna et al., 2015) is based on this theoretical model and includes four evolving experiential positions of engagement based on an individual's role identity, ranging from a passive receiver of care to co-author of care services. An adapted version of this scale was recently used during the COVID-19 emergency (Graffigna et al., 2021); the instrument was shown to be capable of capturing individuals' readiness to cope with the crisis and adhere to the prescribed behavioral changes to contain disease spread.

Starting from these theoretical foundations, we define technology engagement as a process that includes cognitive, affective, and behavioral dimensions that reflect the user's willingness to invest in interactions with technological devices. The model presents four experimental positions (see Figure 1): the first ("Passive Acceptance") indicates the mere use of technology, and the second ("Problematic Use") refers to situations in which the use of technology may be a significant source of stress, the third ("Strategic Use") refers to situations in which users actively use the technology to solve issues and practical problems, and the final ("Perfect Interaction" or "Full Engagement") results from the synthesis between user intention and technology.

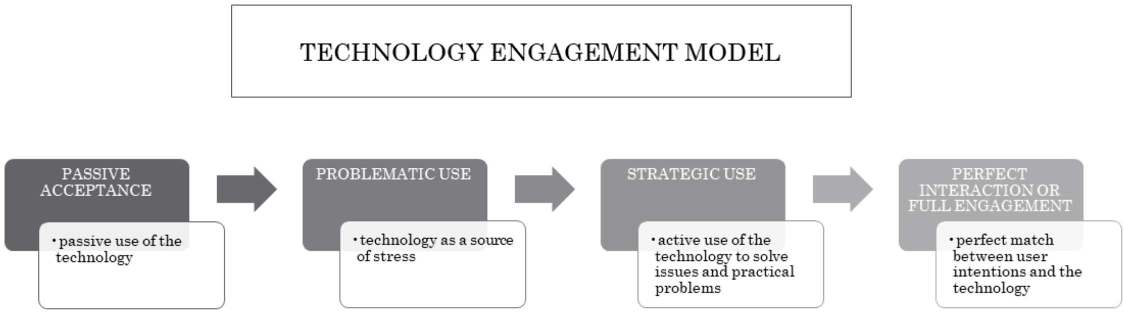

Figure 1. Technology Engagement Model. The model describes four positions: the first ("Passive Acceptance") indicates the mere usage of the technology, the second ("Problematic Use") refers to situations in which the use of technology may be a significant source of stress, the third ("Strategic Use") refers to situations in which users actively use the technology to solve issues and practical problems, and the final one ("Perfect Interaction" or "Full Engagement") results from the perfect match between user intentions and the technology.

As a result, the overall goal of this study is to propose a new instrument, the Technology Engagement Scale, to specifically investigate the process of engagement with technology (TES). More specifically, this study aims to: a. investigate the psychometric properties of the TES; and b. elucidate how the construct of technological engagement as measured by the TES is associated with the other two convergent measures, namely technology acceptance and perceived competence in using technological devices. Finally, we aimed to investigate the prevalence of technology engagement in the current sample and see if there were any differences in the frequency of e-shopping and online leisure activities between the four technology engagement levels during the COVID-19 pandemic (namely, Passive Acceptance, Problematic Use, Strategic Use, and Perfect Interaction or Full Engagement).

2. Methods

2. 1 Sampling and recruitment procedure

This study is part of a broader project ("Behavioural change: prospettive per la stabilizzazione di comportamenti virtuosi verso la sostenibilità") aimed at investigating behavioral changes, habits, and perceptions of people living in Italy during the COVID-19 pandemic. Data were collected in Italy between June 16th and June 25th, 2020. A market research company (Ipsos srl) oversaw the participants' selection and employed a stratified causal sampling strategy according to the following socio-demographic variables: gender, age, geographical area, education level, and employment status. Hence, the sample is representative of the population resident in Italy according to data from ISTAT dating back to 2020. The final sample included 2021 participants. The interviews were carried out using the CAWI method (Computer-Aided Web Interviewing). This study has been performed following the Declaration of Helsinki and has been approved by the ethics committee of Università Cattolica del Sacro Cuore of Milan.

2.2 Study materials

The complete survey was composed of several measures investigating individuals' behavioral changes, habits, and perceptions during the COVID-19 crisis in Italy as part of a larger study (see section 2.1). The specific questionnaires used to investigate the psychometric properties of the TES and its association with the frequency of online activities during the pandemic are reported in this study.

2.2.1 Technology Engagement Scale

As previously explained, the Technological Engagement Scale (TES) was developed as an adaptation of the original PHE-s® (Graffigna et al., 2015) to the relationship with technological devices for evaluating the processual dynamics of the technology engagement, particularly during the challenging time of COVID-19. This scale included five items that explored individuals' engagement with technological devices in everyday situations on a 7-point ordinal scale (see Appendix 1). Participants were asked to think about their experiences of engagement with technology within the context of the current COVID-19 pandemic. Following the engagement continuum of the PHE model, the scale is presented in the labels of the odd-numbered items to describe how the participant may feel about technology. The labels on the right describe higher engagement, whereas the labels on the left describe lower engagement.

2.2.2 Acceptance Technology Model Questionnaire

This questionnaire, based on the first version of the TAM model (Davis, 1985) consists of 9 items presented on a 7-point Likert scale (ranging from "strongly disagree" to "strongly agree") to assess three different aspects of the technology acceptance process. Perceived usefulness assesses people's beliefs about the utility of digital devices in their daily lives (four items). The perceived difficulty in using technological devices is measured by perceived ease of use (four items). The final item assesses the intention to use technology in daily life.

2.2.3. Technology-based Experience of Need Satisfaction – Interface questionnaire (TENS-Interface)

The competence subscale of the Technology-based Experience of Need Satisfaction – Interface questionnaire (TENS-Interface) (Peters, Calvo, & Ryan, 2018) was used to assess perceived competence in the use of technological devices. The TENS Interface is a self-report questionnaire designed to assess whether a product or instrument is perceived by the user as having an impact on his or her psychological well-being in terms of fulfillment of needs for autonomy, competence, and relatedness. The 5-item Competence scale uses a 5-point Likert scale to assess participants' agreement with statements such as "I feel very capable and effective at using technology" (1 = not at all true; 5 = completely true).

2.2.4 e-Shopping and online leisure activities during the COVID-19 pandemic

There were two main online activities: for e-shopping, there were four different product categories (1) grocery shopping (food and cleaning supplies); (2) clothing and accessories purchases; (3) health and beauty purchases; (4) purchasing prepared meals; for online leisure activities, there were four categories: (5) reading and downloading magazines, newspapers, and eBooks; (6) searching for and purchasing travel tickets, hotels, and vacation packages; (7) watching movies and listening to music; and (8) playing videogames. Participants were asked to rate the frequency of their online activities during the COVID-19 pandemic by answering the question "How often did you use the Internet or social media for the following activities in the last year?" on the following frequency options: (1) more than previously, (2) for the first time, (3) as previously (often), (4) as previously (rarely), (5) less than previously, (6) used previously but not this year, and (7) never.

3. Statistical Analysis

The number and frequency for categorical variables, and the mean and standard deviation for the continuous variables, were calculated as descriptive statistics. The five ordinal items of the TES were recoded from a 7-points scale to a 4-points one. Intermediate points were considered as if the participant answered the previous point (i.e., "1" &"2" were recoded as "1", "3" &" 4" were recoded as "2", "5" & "6" were recoded as "3" and "7" was recoded as "4"). Given the ordinal nature of the recoded item, the data analysis involved a suitable technique for ordinal measures. Descriptive statistics (Median and Shannon Entropy Index) of the individual items were calculated to conduct the initial exploration of the data in terms of central tendency and variability. A Categorical Principal Component Analysis (CATPCA) was carried out to explore the factorial structure. The reliability was assessed using the Ordinal Alpha via Empirical Copula Index. A reliability index superior to 0.7, 0.8, and 0.9 can be interpreted as acceptable, good, and excellent, respectively (Bonanomi, Cantaluppi, Nai Ruscone, & Osmetti, 2015). To verify the structure and the unidimensionality of the scale, a confirmatory CFA for ordinal data, and a Rasch Model were performed. For CFA, Goodness of fit indices was evaluated: a good model fit reports a root-mean-square error of approximation (RMSEA) and its 90% confidence interval below <0.08; a standardized root mean square residual (SRMR) <0.08; and a Comparative Fit Index >0.95 [Hu 1999]. In the family of Rasch Models, Partial Credit Model (PCM) was chosen because the revised items had more than two response options with different patterns of usage. The model was estimated by the maximum likelihood method (Andrich, Sheridan, Lyne, & Luo, 2000). The Person Separation Index (PSI) was calculated to evaluate the reliability of the PCM. Values for PSI superior to 0.8 are acceptable (Prieto, Alonso, & Lamarca, 2003; Wright & Masters, 1982). Moreover, to check whether the items fitted the expected model, Infit and Outfit mean square (MNSQ) statistics were computed. If the data fit the PCM, the fit statistics are expected to lie in a range between 0.6 and 1.4 (Wright & Masters, 1982). To assess convergent validity, TES scores were evaluated in their relation to the TAM Scale (Technology acceptance model) and TENS-Interface- Competence subscale.

Finally, to evaluate the association between the frequency of online activities and different technology engagement levels (namely, Passive acceptance, Problematic Use, Strategic Use, and Perfect Interaction or Full Engagement), a series of contingency tables was created. Pearson's chi-square tests were also carried out to reject the null hypothesis that data are randomly distributed across technology engagement levels. As post-hoc, standardized residuals were inspected: standardized residuals were calculated as the difference between observed and expected counts of a cell divided by an estimate of its standard deviation. Since they are asymptotically normally distributed with a mean of 0 and standard deviation of 1 under the null hypothesis of independence, as a general rule of thumb, cells with an absolute value of standard residuals above 2 can be considered to significantly contribute to the general chi-square value (Haberman, 1973). All analyses have been carried out with IBM SPSS 23 (release 23.0.0.0).

4. Results

4.1 Sample

Male participants were 955 (47.3%). The mean age was 49.2 years (SD = 16.5; range 18–90). For a more detailed description of the study sample, see Table 1.

	N	%
Gender		
Male	955	47.3
Female	1066	52.7
Age		
18-30	313	15.5
31-50	747	37.0
51-65	507	25.1
Over 55	454	22.5
Geographic area		
North-West	535	26.5
North-East	376	18.6
Center	404	20.0
South	475	23.5
Islands	231	11.4
Education		
Middle school or lower	432	21.4
High School	817	40.4
University degree	772	38.2
Employment status		
Yes	993	49.1
No	1028	50.9

Table 1. Demographic characteristics of the sample (N = 2021).

4.1 Descriptive statistics

There were no missing data in our dataset. Table 2 shows descriptive statistics of all items of our instruments (median, range, frequency distribution) as well as their Shannon Entropy Index.

Item	Rank Range	Median	Shannon Entropy	Frequency Distribution (%)			
				1	2	3	4
TES 1	1-4	3	0.776	2.2%	18.9%	54.1%	24.9%
TES 2	1-4	3	0.772	2.1%	15.4%	52.4%	30.0%
TES 3	1-4	3	0.809	2.9%	17.3%	48.4%	31.4%
TES 4	1-4	3	0.86	4.0%	21.9%	41.5%	32.6%
TES 5	1-4	3	0.829	4.0%	20.9%	49.9%	25.2%

Table 2: Item-level descriptive statistics for ranks on the TES item scale (N=2021)

The validation study involved 2021 participants. The sample was divided into two subgroups: Group 1(n = 1024, about 60%) was used to conduct the exploratory analysis, and Group 2 (n = 817, about 40%) was used to conduct the confirmatory analysis. The two groups do not show significant differences in the main socio-demographic variables.

4.2 Exploratory categorical principal component analysis

An exploratory categorical principal component analysis (CATPCA) was conducted on Group 1 without any restriction on the number of metric factors to be estimated. The analysis yielded one factor with an eigenvalue of 3.55, which exceeds the Kaiser Criterion of 1, explaining 71.0% of the total variability. No other factor has an eigenvalue superior to 1. The items showed a very good internal consistency since the value of the Ordinal Alpha via Empirical Copula was equal to 0.853. Each item contributed significantly to the scale score. So, the internal consistency of the TES was satisfactory. Table 3 shows the factor loadings for the one solution. All factor loadings had a very high value (> 0.8), confirming the unidimensionality of the scale.

Item	Factor loadings
TES 1	.854
TES 2	.814

TES 3	.862
TES 4	.842
TES 5	.842

Table 3. Factor loadings from CATPCA – one-factor solution.

4.3 Confirmatory Factorial Analysis

A Confirmatory Factor Analysis (CFA) was performed on Group 2. The estimation method was asymptotically distribution-free, particularly suitable for ordinal data not-Gaussian distributions. To test the model, each variable was allowed to load on only one factor, and one variable loading in the latent factor was fixed at 1.0. For the remaining factor loadings, residual variances were freely estimated. CFA showed adequate goodness of fit indices: CFI = 0.997, SRMR = 0.007, RMSEA = 0.044 (90% C.I.: 0.010–0.078). These values suggested that the model is coherent with the data. Table 4 shows the standardized regression weights between the latent construct and the observed items. All the observed items' variabilities seem to be well explained by the latent factor, with standardized estimates ranging between 0.725 and 0.836.

Item	Standardized Estimate
TES 1	0.764*
TES 2	0.725*
TES 3	0.836*
TES 4	0.795*
TES 5	0.752*

Table 4. Standardized regression weights in the CFA.

4.4 Rasch Model

Table 5 shows the results of the PCRM to test the psychometric properties of the TES scale. The item statistics ranged from .685 to 0.866 for the outfit MNSQ and from .711 to 0.884 for the infit MNSQ. MNSQ determines how well each item contributes to defining a single underlying construct (uni-dimensionality). These values indicate an acceptable fit of the Rasch Model. The distances between subsequent thresholds showed an acceptable distinction between the response options and measurement model fit. The Person Separation Index for the TES scale was equal to 0.819, superior to the acceptability cut-off. Rasch Model confirmed the unidimensionality of the TES scale and the fit of each item of the scale to the data.

	Location (SE)	**Step 1**	**Step 2**	**Step 3**	**Outfit MNSQ**	**Infit MNSQ**
TES 1	1.131 (0.184)	-2.603	0.726	5.269	0.745	0.782
TES 2	0.84 (0.186)	-2.524	0.328	4.714	0.866	0.884
TES 3	1.029 (0.165)	-2.113	0.644	4.557	0.685	0.711
TES 4	1.298(0.152)	-1.784	1.314	4.365	0.716	0.726
TES 5	1.519 (0.154)	-1.764	1.115	5.205	0.839	0.857

Table 5. Results of Partial Credit Rasch Model

4.5 Convergent validity

To assess convergent validity, TES factor scores were evaluated in relation to TAM Scale (Technology acceptance model) and TENS-Interface - Competence subscale by using the Pearson correlation coefficients. The results showed a strong correlation between TES and all three dimensions of TAM scale: Perceived Usefulness ($r = 0.664$, $p < 0.001$); Perceived Ease of Use ($r = 0.755$, $p < 0.001$); Intention of Use ($r = 0.642$, $p < 0.001$). Moreover, there was a strong correlation between TES and TENS-Interface- Competence subscale ($r = 0.655$, $p < 0.001$).

4.6 Descriptive statistics, scoring, and cut-off

After normalizing the Rasch scores to fit into a 0–100 scale, the scores show a rather normal distribution (mean=65.22, standard deviation= 21.49, skewness=-0.119, kurtosis=-0.454). According to the PHE model, four groups were then identified, namely below -1 std. deviation, between -1 std. deviation and the mean, between the mean and +1 std. deviation, and above +1 standard deviation. Table 6 shows the percentage of participants in each group.

TES group	% in the sample
Passive acceptance	20.6%
Problematic use	36.5%
Strategic use	23.2%
Perfect interaction or full engagement	19.7%

Table 6. Percentage of participants in each TES group.

4.7 Online behaviors and technology engagement

Table 7 summarizes the results of the contingency tables. Pearson's chi-squared analysis and standardized residual inspection revealed that different levels of technology engagement are significantly associated with different frequencies of online behaviors. In more detail, our findings revealed that people with lower levels of engagement responded more frequently that they never used the Internet or social networks for online leisure activities or e-shopping. On the other hand, individuals with a higher level of engagement responded more frequently that they used technology for these online activities "more than previously."

e-Shopping	TES Levels		more than previously	for the first time	as previously (often)	as previously (rarely)	less than previously	used in past but not this year	never	Total
Grocery shopping. Chi-square= 22,014 (df= 18),p=0.231	**Passive Acceptance**	% Within row	13.4%	5.3%	31.9%	13.6%	3.5%	2.0%	30.3%	100%
		Std. res	-1.6	-1.2	0.4	-0.5	1.3	1.8	1.0	
	Problematic Use	% Within row	16.0%	6.5%	30.9%	16.0%	2.1%	0.7%	27.9%	100%
		Std. res	-0.3	-0.2	0.0	1.1	-0.7	-1.1	0.0	
	Strategic Use	% Within row	18.2%	8.7%	30.0%	14.3%	2.7%	1.1%	24.9%	100%
		Std. res	0.9	1.7	-0.3	-0.1	0.2	0.1	-1.2	
	Perfect Interaction or Full Engagement	% Within row	19.0%	6.3%	31.0%	12.5%	1.9%	0.8%	28.5%	100%
		Std. res	1.2	-0.3	0.0	-1.0	-0.8	-0.5	0.2	
	% Within row		16.4%	6.7%	30.9%	14.4%	2.5%	1.1%	27.9%	100%
Clothes and accessories. Chi-square= 69,024 (df= 18),p<0.001	**Passive Acceptance**	% Within row	11.0%	4.2%	20.0%	31.9%	9.7%	3.3%	19.8%	100%
		Std. res	-1.8	0.5	-1.3	1.5	-1.8	0.0	**2.8**	
	Problematic Use	% Within row	11.5%	4.8%	23.8%	26.0%	14.8%	2.4%	16.8%	100%
		Std. res	**-2.0**	1.5	0.5	-1.2	1.6	-1.3	1.4	
	Strategic Use	% Within row	18.6%	2.7%	21.1%	28.9%	14.3%	3.6%	10.8%	100%
		Std. res	**2.4**	-1.1	-0.9	0.3	1.0	0.4	**-2.2**	
	Perfect Interaction or Full Engagement	% Within row	18.7%	2.2%	27.4%	27.6%	10.3%	4.6%	9.2%	100%
		Std. res	**2.3**	-1.5	1.7	-0.2	-1.4	1.4	**-2.8**	
	% Within row		14.3%	3.7%	23.0%	28.3%	12.7%	3.3%	14.8%	100%
Health & Beauty. Chi-square= 44,842 (df= 18),p<0.001	**Passive Acceptance**	% Within row	8.6%	3.1%	24.0%	26.0%	7.3%	2.4%	28.6%	100%
		Std. res	**-3.1**	-0.4	-0.5	0.2	0.8	0.8	**2.3**	
	Problematic Use	% Within row	13.4%	4.0%	24.9%	24.5%	6.4%	1.3%	25.5%	100%
		Std. res	-0.4	0.9	-0.2	-0.6	0.1	-1.1	1.1	

	Strategic Use	% Within row	16.1%	3.1%	24.4%	27.4%	7.6%	2.2%	19.1%	100%
		Std. res	1.2	-0.3	-0.4	0.7	1.1	0.6	-1.9	
	Perfect Interaction or Full Engagement	% Within row	19.0%	3.0%	28.7%	25.5%	3.5%	1.9%	18.4%	100%
		Std. res	**2.6**	-0.5	1.3	-0.1	**-2.1**	0.0	**-2.0**	
	% Within row		14.0%	3.4%	25.3%	25.6%	6.3%	1.9%	23.5%	100%
Prepared meal. Chi-square= 53,816 (df= 18),p<0.001	**Passive Acceptance**	% Within row	7.3%	5.1%	11.7%	22.5%	5.7%	2.0%	45.8%	100%
		Std. res	**-2.6**	0.2	0.0	0.9	-1.2	-0.7	1.4	
	Problematic Use	% Within row	10.4%	5.0%	12.5%	16.5%	8.1%	2.8%	44.8%	100%
		Std. res	-0.9	0.2	0.6	**-2.5**	0.8	0.5	1.3	
	Strategic Use	% Within row	12.8%	4.7%	9.4%	23.4%	9.2%	3.8%	36.6%	100%
		Std. res	0.9	-0.1	-1.4	1.3	1.5	1.7	-1.7	
	Perfect Interaction or Full Engagement	% Within row	17.1%	4.3%	12.8%	23.1%	5.2%	1.1%	36.4%	100%
	% Within row		11.4%	4.9%	11.7%	20.5%	7.3%	2.5%	41.7%	
<u>Leisure activities</u>										
Newspapers & eBooks. Chi-square= 76,403 (df= 18),p<0.001	**Passive Acceptance**	% Within row	9.5%	4.2%	17.2%	19.2%	8.6%	1.5%	39.7%	100%
		Std. res	**-2.9**	0.5	-2.1	-0.4	2.2	-1.1	**3.2**	
	Problematic Use	% Within row	13.6%	4.1%	23.1%	18.4%	3.7%	3.2%	33.9%	100%
		Std. res	-0.8	0.5	0.8	-1.1	**-2.6**	1.5	1.2	
	Strategic Use	% Within row	16.9%	4.7%	23.8%	22.2%	7.2%	2.0%	23.1%	100%
		Std. res	1.2	1.0	0.9	1.0	1.0	-0.4	-3.1	
	Perfect Interaction or Full Engagement	% Within row	20.4%	1.4%	22.0%	22.3%	6.3%	1.9%	25.8%	100%
		Std. res	**2.9**	**-2.4**	0.1	0.9	0.2	-0.5	**-1.9**	
	% Within row		14.6%	3.8%	21.8%	20.1%	6.0%	2.3%	31.4%	100%
Travel. Chi-square= 59,271 (df= 18),p<0.001	**Passive Acceptance**	% Within row	3.5%	3.5%	11.9%	14.5%	16.3%	12.5%	37.8%	100%
		Std. res	-0.9	1.4	-0.6	-1.1	-1.8	-2.0	**4.3**	
	Problematic Use	% Within row	3.5%	2.7%	11.7%	17.7%	20.2%	16.6%	27.7%	100%

		Std. res	-1.2	0.3	-0.9	0.7	0.1	0.2	0.2	
	Strategic Use	% Within row	4.7%	1.8%	13.5%	15.9%	22.9%	19.3%	22.0%	100%
		Std. res	0.4	-0.9	0.3	-0.4	1.4	1.5	*-2.2*	
	Perfect Interaction or Full Engagement	% Within row	6.8%	1.6%	16.0%	17.9%	20.7%	16.8%	20.1%	100%
		Std. res	**2.2**	-1.0	1.7	0.6	0.3	0.2	**-2.6**	
	% Within row		4.4%	2.5%	12.9%	16.6%	20.0%	16.3%	27.3%	100%
Movies & Music Chi-square= 121,185 (df= 18),p<0.001	**Passive Acceptance**	% Within row	15.8%	4.2%	21.3%	18.4%	6.4%	2.6%	31.4%	100%
		Std. res	**-4.2**	1.3	-2.1	1.3	**2.4**	0.4	**4.1**	
	Problematic Use	% Within row	22.8%	2.8%	25.8%	15.8%	4.1%	3.1%	25.6%	100%
		Std. res	-1.6	-0.4	-0.2	-0.2	0.0	1.2	1.9	
	Strategic Use	% Within row	31.6%	3.4%	27.1%	17.0%	3.6%	1.8%	15.5%	100%
		Std. res	2.4	0.4	0.4	0.5	-0.5	-0.8	-3.1	
	Perfect Interaction or Full Engagement	% Within row	37.4%	1.9%	32.0%	12.5%	1.9%	1.4%	13.0%	100%
		Std. res	**4.4**	-1.3	2.2	-1.7	-2.1	-1.3	**-3.8**	
	% Within row		25.8%	3.1%	26.2%	16.1%	4.1%	2.4%	22.4%	100%
Video games. Chi-square= 83,639 (df= 18),p<0.001	**Passive Acceptance**	% Within row	9.7%	2.6%	16.3%	15.0%	4.8%	2.0%	49.6%	100%
		Std. res	**-3.5**	0.6	-1.2	-0.6	-0.5	-1.5	**4.0**	
	Problematic Use	% Within row	14.5%	2.4%	18.6%	14.9%	6.3%	3.3%	40.0%	100%
		Std. res	-1.3	0.3	0.0	-0.9	1.0	0.2	1.0	
	Strategic Use	% Within row	19.1%	2.2%	20.2%	17.3%	4.0%	3.8%	33.4%	100%
		Std. res	1.4	0.0	0.7	0.6	-1.3	0.7	-1.5	
	Perfect Interaction or Full Engagement	% Within row	25.1%	1.4%	20.0%	18.9%	6.2%	3.8%	24.6%	100%
			4.2	-1.1	0.6	1.3	0.6	0.6	**-4.2**	
	% Within row		16.4%	2.2%	18.7%	16.2%	5.4%	3.2%	37.9%	100%

Table 7. Results of contingency tables.

6. Discussion

The main objective of this study is to introduce and validate a brief 5-item instrument (namely, the Technology Engagement Scale - TES) to measure the processual dynamics of psychological engagement towards technology in a representative sample of 2021 participants. The TES is theoretically based on a description of engagement as a "processual" experience that was first used in the field of chronic care to describe patients' interactions with their illnesses and their management. (Bombard et al., 2018; Graffigna & Barello, 2018; Zullig & Bosworth, 2017). Accordingly, the 5-item TES has been developed as an adaptation of the original Patient Health Engagement Scale (PHE_s®) (Graffigna et al., 2015) to the relationship with technological devices for evaluating the dynamics of engagement with technology in four experiential positions: passive acceptance, problematic use, strategic use and the perfect interaction of full engagement.

Results obtained from the exploratory categorical principal component analysis (CATPCA) revealed one factor, which was then evaluated in the subsequent Confirmatory Factor Analysis (CFA) and Rasch Model analysis, confirming the mono-dimensionality of the TES. Furthermore, empirical ordinal alpha indicated that TES has a good internal consistency.

We assessed the questionnaire's convergent validity by investigating the correlations between the TES scores and the three subscales of the Technology Acceptance Model (TAM), as well as the subscale assessing perceived competence in using technological devices (namely, the Competence subscale from the Technology-based Experience of Need Satisfaction - Interface questionnaire). The results revealed strong and positive correlations, indicating that the proposed questionnaire has good convergent validity. These correlations are consistent with the predictions of one of the most relevant models in the field of user engagement (O'Brien & Toms, 2010). According to the authors, various variables such as challenge, aesthetic and sensory appeal, feedback, novelty, interactivity, perceived control and time, awareness, motivation, interest, and affect could all play a role in promoting engagement. Some of these attributes referred to the *pragmatic* qualities of technology interaction; these components have traditionally been investigated in HCI literature (Davis, 1985; Lee, Kozar, & Larsen, 2003). Other attributes, on the other hand, referred to affective components as a requirement for user engagement. These components, in particular, have been investigated in recent theoretical frameworks that combine HCI studies and positive psychology, such as Positive Technology (Riva, Baños, Botella, Wiederhold, & Gaggioli, 2012) and Positive Computing (Calvo & Peters, 2014; Gaggioli, Riva, Peters, & Calvo, 2017). In this vein, the relationship between the TENS-Interface questionnaire's Competence Subscale and TES scores captures the relationship between the perceived impact of technology on psychological wellbeing in terms of fulfillment of the need for competence and the process of engagement with technology.

Another important objective of this work was to evaluate potential associations between the four technology engagement levels (namely, Passive Acceptance, Problematic Use, Strategic Use, and Perfect Interaction or Full Engagement) and the frequency of online activities during the COVID-19 crisis. The pandemic and related social distancing measures are transforming all aspects of our individual and social lives (Gruber et al., 2020; Townsend, Hawley, Stephenson, & Williams, 2020). To avoid a complete disruption of daily life, many activities have rapidly shifted online rather than physically, resulting in an impressive diffusion of digital technologies in almost all sectors of society (Budd et al., 2020; Golinelli et al., 2020; Mouratidis & Papagiannakis, 2021). In terms of daily use, a recent systematic review (Vargo et al., 2021) indicated that the importance and the frequency of engaging in telework, teleconferencing, e-learning, telehealth, and online shopping significantly increased during the COVID-19 pandemic (see also (Erjavec & Manfreda, 2022). In addition, online leisure activities (reading news, magazine, and searching for vacation) and home-based entertainment (e.g., streaming TV, movies, music, and playing video games) have grown in popularity (van Leeuwen, Klerks, Bargeman, Heslinga, & Bastiaansen, 2020). Our results revealed that individuals with lower levels of engagement responded more frequently that they never used the Internet or social networks for online leisure activities or online shopping. On the other hand, individuals with a higher level of engagement responded more frequently that they used technology for these online activities "more than previously". Globally, these findings indicated that TES levels could predict the frequency of online activities during the COVID-19 pandemic, implying that engagement has a significant impact on the use of technology in a pandemic situation. Future research could thus concentrate on elucidating the potential role of technology engagement in predicting online behaviors without specifically referencing the pandemic.

6.1 Limitations

The presented research also has some limitations. First, we did not investigate the scale in terms of test-retest reliability and criterion-related validity. Second, the data were collected during the COVID-19 pandemic, when there is the widespread use of technology for most daily activities. Future research could therefore focus on validating the theoretical model presented in this study beyond the period of the pandemic.

6.2 Conclusion

Understanding how we interact with digital technologies in everyday life, as well as how to sustain engaging technologically mediated experiences, is a significant theoretical and methodological challenge. Our findings provide preliminary evidence in support of using TES to assess the complex dynamics of engagement with technological devices in a simple, quick, and easy-to-administer manner. As a result, this scale could be a useful tool for assessing user engagement with technology for HCI researchers and communication scholars, as well as in applied and everyday settings. Although more research on the scale is needed, preliminary evidence suggests that the TES has good psychometric properties and can be used in both research and applied settings.

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Author contribution

Conceptualization: SS and GR. Methodology: SS, AB, GG, and GR. Statistical Analysis: AB and LP. Initial Draft: SS. Revision: AB, LP, GG, and GR. Funding: GR.

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Figure Captions

Figure 1. Technology Engagement Model. The model describes four positions: the first ("Passive Acceptance") indicates the mere usage of the technology, the second ("Problematic Use") refers to situations in which the use of technology may be a significant source of stress, the third ("Strategic Use") refers to situations in which users actively use the technology to solve issues and practical problems, and the final one ("Perfect Interaction" or "Full Engagement") results from the perfect match between user intentions and the technology.