Exploring Technology Readiness Among Finnish University Students

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Abstract: New technologies have the potential to support inclusive and collaborative learning processes. However, students' technology readiness influences how they utilize learning technologies. This research examined technology readiness among Finnish university students (N = 796) utilizing Technology Readiness Index TRI 2.0, which showed promising psychometric properties in a student sample. Latent class analysis was used to obtain profiles with different characteristics. Our findings provide encouraging evidence that TRI 2.0 could be a valuable explanatory variable in modeling the use of educational technology.

Introduction

Technology's growing role and increased use of technology-based systems impose requirements for dealing and communicating with new technologies in work, study, and everyday life. New technologies have the potential to support inclusive and collaborative learning processes (e.g., Miller et al., 2021). However, students need technical and cognitive support for using new technologies in their learning processes (e.g., Bielik et al., 2021). Specifically, technology readiness (TR) is an influential construct to consider in computer-mediated teaching and learning practices (e.g., Li, 2018; Tang, 2021). The construct of TR means "people's propensity to embrace and use new technologies for accomplishing goals in home life and at work" (Parasuraman 2000, p. 308). For example, TR has a positive influence on learning motivation in blended learning (Geng et al., 2019), it influences how students assess digital learning environments (Reyes-Mercado et al., 2022), and it is associated with online learning readiness (Tang, 2021). In general, TR is an essential construct when examining the adoption and use of new technologies (Blut & Wang, 2020). Dishon (2022, pp. 460, 468) proposes that the fields of learning sciences and computer-supported collaborative learning should examine "how new technologies reshape learning by introducing new tensions and opportunities" instead of reproducing "existing practices and disparities." Therefore, it would be valuable to consider the learners' TR with both enabling *and* inhibiting factors of technology use when examining technology-enhanced learning, especially in a cross-cultural context (e.g., Kaushik & Agrawal, 2021). Our research examined TR among Finnish university students utilizing the Technology Readiness Index (TRI) 2.0 (Parasuraman & Colby, 2015). The main contributions of the research relate to i) deepening the understanding of quantitative associations of TR with other constructs and ii) examining the enabling and inhibiting factors of TR among Finnish university students to advance cross-cultural research examining TR in the learning sciences and technology-enhanced learning.

Materials and methods

The sample consisted of students (N = 796) studying in a Finnish public multidisciplinary research university (ISCED 2011 level 6–8). The age of the respondents ranged from 17–73 years (Mdn = 25, M = 27.6, SD = 8.9). An open-ended form field was used to ask about gender, and 519 (65%) of the respondents identified themselves as women, 264 (33%) as men, 7 (1%) as nonbinary, and 6 (1%) that were unknown were coded as missing values. TRI 2.0 (Parasuraman & Colby, 2015) was the main instrument used to measure TR. TRI has four dimensions: optimism (OPT), innovativeness (INN), discomfort (DIS), and insecurity (INS) (Parasuraman & Colby, 2015). The Finnish translation of TRI 2.0 (Table 1) involved a professional forward-backward translation utilizing a committee approach (Brislin et al., 1973, pp. 46–47). We conducted a psychometric analysis of TRI utilizing classical test theory and factor analysis following an approach in Heilala et al. (2022b). For the latent class analysis (LCA) (Hagenaars & McCutcheon, 2002), the smallest sample-size adjusted BIC (Whittaker & Miller, 2021) and the *a priori* theoretical model (Parasuraman & Colby, 2015) were used to select the number of classes. Affinity for Technology Interaction (ATI) scale (Franke et al., 2019; Heilala et al., 2022b) was used to assess the convergent and discriminant validity of TRI and its dimensions. ATI is a unidimensional instrument measuring affinity for technology interaction, which means "whether users tend to actively approach interaction with technical systems or, rather, tend to avoid intensive interaction with new systems" (Franke et al., 2019, p. 1). Diverse Technology Use Index (D-TUI) is a novel instrument that aims to quantify the use of common and more specialized technologies, and it was used to examine the validity of TRI. To construct D-TUI, respondents are asked to name five technical systems (including apps and devices) they have used during the last week. D-TUI of a person i is:

$$\text{D-TUI}_i = \sqrt{\sum_{j=1}^{5} \frac{1}{n_{ij}}},$$

where n_{ij} is the total frequency of j:th technology in the whole sample mentioned by person i. D-TUI is standardized and min-max normalized between [0, 1]. Values closer to 0 indicate that the respondent has listed similar common technologies as other respondents. In other words, a higher D-TUI value indicates that the respondent has reported using more specialized technologies. The square root compensates for the positive skewness of D-TUI because common technologies are mentioned more often.

Table 1
The Finnish version of the TRI 2.0. The original English TRI 2.0 and items, see Parasuraman & Colby (2015).*

OPT1	Uudet teknologiat vaikuttavat elämänlaadun paranemiseen.
OPT2	Teknologia antaa minulle enemmän liikkumavapautta.
OPT3	Teknologia lisää ihmisten oman arjen hallintaa.
OPT4	Teknologia tekee minusta omassa elämässäni tuotteliaamman.
INN1	Muut kysyvät minulta neuvoa uusiin teknologioihin liittyvissä asioissa.
INN2	Ystäväpiirissäni hankin yleensä ensimmäisten joukossa uutta teknologiaa sen tullessa saataville.
INN3	Pystyn yleensä ottamaan selvää uusista korkean teknologian tuotteista ja palveluista ilman muiden apua.
INN4	Pysyttelen ajan tasalla uusimmasta teknologisesta kehityksestä niillä aloilla, joista olen kiinnostunut.
DIS1	Kun saan teknistä tukea korkean teknologian tuotteen tai palvelun tarjoajalta, minusta tuntuu joskus, että joku minua enemmän tietävä yrittää hyötyä minusta.
DIS2	Teknisen tuen palveluista ei ole apua, koska asioita ei selitetä niin että minä ymmärtäisin.
DIS3	Joskus minusta tuntuu siltä, että teknisiä järjestelmiä ei ole suunniteltu tavallisten ihmisten käytettäviksi.
DIS4	Selkokielisiä korkean teknologian tuotteiden tai palveluiden käyttöoppaita ei ole olemassakaan.
INS1	Ihmiset ovat liian riippuvaisia siitä, että teknologia tekee asioita heidän puolestaan.
INS2	Liika teknologia häiritsee ihmisiä haitaksi asti.
INS3	Teknologia heikentää ihmissuhteiden laatua vähentämällä henkilökohtaista vuorovaikutusta.
INS4	Tunnen oloni epävarmaksi asioidessani tai käydessäni kauppaa sellaisten tahojen kanssa, jotka ovat tavoitettavissa vain verkon välityksellä.
	Likert options: vahvasti eri mieltä (1), jokseenkin eri mieltä (2), ei samaa eikä eri mieltä (3), jokseenkin samaa mieltä (4), vahvasti samaa mieltä (5)

Results

The Finnish translated version of TRI replicated the original (a priori) four-factor model showing a sufficiently good fit (Table 2). A measurement invariance by gender was assessed by evaluating a series of multi-groups CFA models. The models showed that the factor loadings were equal (i.e., metric invariance, weak invariance). When items INN2, INS1, and four thresholds were released to vary between groups, the model showed partial strong invariance. As a result, the estimates showed no differences in latent dimensions of optimism and insecurity between genders. The lower bound to the reliability of the translated version using coefficient α ranged from 0.65–0.78, closely comparable with the original study (i.e., Parasuraman & Colby, 2015). The stratified coefficient α for the overall TRI showed good reliability (α = 0.86).

Table 2
Categorical CFA models of the Finnish version of TRI 2.0

Model	χ^2	df	χ^{2*}_{diff}	Δdf^*	p^*_{diff}	RMSEA [90% CI]	SRMR	CFI	TLI
A priori	431.1	98				.065 [.059—.072]	.052	.95	0.93
Measurement invariance by gender									
Equal form	516.9	196				.065 [.058—.072]	.058	.94	0.93
Equal loadings	504.8	208	11.6	12	.480	.060 [.054—.067]	.060	.95	0.94
Partial equal thresholds	572.6	246	50.5	38	.085	.058 [.052—.065]	.059	.94	0.94
Equal thresholds	652.2	252	54.8	6	.000	.064 [.058—.070]	.060	.93	0.93

Note: * a scaled chi-square difference test (Satorra & Bentler, 2001)

The validity of the translated version was assessed in terms of convergent and discriminant validity using the ATI scale as the comparison instrument. Sufficient convergent associations (i.e., Carlson & Herdman, 2012) were identified relating to ATI. ATI and INN showed a strong association (r = 0.67). Also, ATI and the overall TRI showed a strong association (r = 0.69). The discriminant validity of the DIS and INS dimensions was supported by their negative associations with ATI (both r = -0.30). As expected, optimism and innovativeness showed a negative association with discomfort and insecurity. D-TUI was used to examine whether the respondents used very common or more specialized technology. Based on the Pearson correlation coefficient, D-TUI showed a small positive correlation between TRI (r = 0.14) and ATI (r = 0.16), indicating they are both associated with actual technology use. Even though the correlation is small, the finding is interesting because it describes the association between a latent trait and actual reported behavior. The result indicates that persons with higher TRI and ATI use more specialized technologies, which provides validity evidence for both TRI and ATI.

The overall mean TRI value in the sample was 3.3 (SD = 0.5). The difference between men (M = 3.5, SD = 0.6) and women (M = 3.2, SD = 0.5) in overall TRI was statistically significant, $p < .001$. A latent class analysis was conducted utilizing all the 16 item variables of the translated version of the TRI. The smallest sample-size adjusted BIC (Whittaker & Miller, 2021) suggested a six-class solution (ABIC = 33704), while the five-class solution (ABIC = 33715) and the seven-class solution (ABIC = 33716) were very close candidate solutions. The original authors of the index used a five-class solution (Parasuraman & Colby, 2015). Therefore, the five-class solution was selected to allow comparability with the latent class structure suggested by the original authors. The latent class analysis identified all original classes: hesitators (27 %), skeptics (21 %), pioneers (19 %), and avoiders (14%). Interestingly, the share of latent classes varied in terms of respondents' fields of studies. For example, in IT, hesitators were the smallest class but in humanities, education, and sports it was the largest class.

Discussion and conclusion

Our research examined TR (Parasuraman & Colby, 2015; Blut & Wang, 2020), which is an influential trait-like property of students affecting the utilization of new technologies (e.g., Li, 2018; Tang, 2021; Geng et al., 2019; Reyes-Mercado et al., 2022). Thus, valid instruments are needed to examine TR in the context of technology-enhanced learning. The Finnish version of TRI 2.0 showed promising psychometric properties in a sample of university students: It replicated the original construct structure and showed measurement invariance in terms of gender. The individual four dimensions showed sufficient lower bounds to reliability. Also, the associations with ATI and D-TUI showed evidence of convergent and discriminant validity of the dimensions and the overall TRI.

TR seems to significantly influence technology adoption (Damerji & Salimi, 2021). Also, the adoption and use of new technologies seem to be associated with adults' technology-related skills; for example, home and work-related use of technologies seem to reduce the probability of having weak problem-solving skills in technology-rich environments and increase the likelihood of strong skills (Hämäläinen et al., 2019). The current technologisation of society is changing the need for learning. The adoption and use of technologies have become, above all, an issue of social equity. Because TR can influence the adoption and use of technologies (Kaushik & Agrawal, 2021), from an equality and inclusive point of view, it would be vital to ensure that all students have opportunities to utilize new learning technologies. The enabling factors—optimism and innovativeness—are essential for students to adopt new learning technologies (e.g., Reyes-Mercado et al., 2022; Kaushik & Agrawal, 2021). Regarding practical implications, our findings support the proposition that students' innovativeness should be supported to enhance their use of digital learning technologies. On the other hand, not all university teachers are necessarily technologically ready to support innovativeness. For example, while teaching professionals seem to generally hold positive attitudes towards the use of digital technologies and feel confident in their skills, in reality, they lack skills regarding adopting and using technologies based on measured outcomes (Hämäläinen et al., 2019). To support teachers, we propose that, for example, learning analytics could be used to provide information to the teachers relating to their own and their students' capabilities in utilizing new learning technologies (e.g., Heilala et al., 2022a).

In summary, our findings provide encouraging evidence that TRI 2.0 could be a valuable explanatory variable in modeling the use of educational technology. The relatively large sample covered a broad range of fields of study, thus, sufficiently representing Finnish university students. However, generalizability to the general population is limited. Future studies could, for example, examine the predictive validity of TR. For example, can an intervention enhancing technological innovativeness shift students' stance towards higher TR and promote technology-enhanced learning? Lastly, we propose that to ensure equitable and inclusive use of new technologies in learning, teachers and educational institutions should i) provide access to new learning technologies, ii) provide examples of innovative use of learning technologies, and iii) promote an encouraging atmosphere where innovative use of learning technologies can flourish.

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