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Mapping AI learning readiness self-efficacy worldwide: Scale validation and cross-continental patterns

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ABSTRACT

In today's world, knowing how to use artificial intelligence (AI) technologies is becoming an essential skill. While methods for measuring the perceived efficacy of AI use are emerging, brief measures of users' self-evaluated learning and self-efficacy regarding AI use are still lacking. This study aimed to validate the five-item AI Learning Readiness Self-Efficacy (AILRSE) scale and examine cross-national differences between 12 countries on six continents. We used large-scale, adult population samples from Australia, Brazil, Finland, France, Germany, Ireland, Italy, Japan, Poland, Portugal, South Africa, and the United States collected in 2024–2025 (N = 20,173), enabling both cross-sectional and longitudinal analysis. Scale validation involved confirmatory factor analysis and measurement invariance testing across countries and over time. The results supported a one-factor structure with high internal consistency and scalar invariance across countries as well as strict invariance in Finnish cross-sectional and longitudinal data. AI positivity emerged as the strongest predictor of AILRSE-5 scores across all models, followed by younger age and more frequent use of text-to-text AI tools (e.g., ChatGPT, Copilot). Education and gender effects were small and context dependent. The findings indicate that AILRSE-5 is a brief, reliable, and valid tool for assessing self-efficacy in AI learning readiness. Its invariance across diverse national contexts supports its applicability in cross-cultural research, while its longitudinal invariance suggests stability over time. Furthermore, our results provide rare cross-national evidence on the individual factors shaping AI learning readiness self-efficacy. The study advances understanding of how people adapt to the rapidly evolving AI landscape.

1. Introduction

Recent years have shown remarkable development in artificial intelligence (AI) and tools made for personal and professional use. AI is transforming work life by taking over tasks that can be made more efficient through automation, such as data entry, data processing, analysis, and customer service. At the same time, it creates space for employees to focus on high-value activities or tasks that require uniquely human abilities (AlQato, 2024; Getman et al., 2024). Certain sectors, including education, are also currently deeply affected by the wide availability of generative AI tools (Ansari et al., 2024; Chiu, 2024). Besides work and education, AI tools are becoming common in leisure activities, including intelligent and autonomous domestic tools and robots (Butaney et al., 2025; Kang & Kim, 2025), virtual assistants (Johnson & Reimer, 2023), and chatbot friends (Brandtzaeg et al., 2022; Skjuve et al., 2021). AI development is expected to continue in the upcoming years, providing new tools for daily life, especially in technologically advanced countries (Khogali & Mekid, 2023).

As AI is no longer limited to a single field or profession, skills and readiness to use AI technologies are becoming crucial for an increasing proportion of society. Both barriers to and facilitators of AI adoption therefore need to be better understood. It is also important to investigate how users can use AI in an optimal way, harnessing its full potential. Motivation to acquire AI skills, to use AI, and to feel confident in doing so are likely to be key factors in AI adoption. To investigate these questions, however, reliable and valid instruments are required. In

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particular, self-efficacy—the belief in one's capacity to succeed in a specific task (Bandura, 1986, 1997)—may be a significant factor in explaining adoption and engagement with AI technologies. Previous research has demonstrated the role of self-efficacy in technology use (Eastin & LaRose, 2000; Latikka et al., 2019), but validated measures tailored to AI, along with a deeper understanding of its specific role in AI use and learning, are still needed.

This article addresses this gap by investigating AI learning readiness self-efficacy (AILRSE). Specifically, our first aim is to validate a five-item AI Learning Readiness Self-Efficacy scale (AILRSE-5). The second aim is to examine cross-national patterns associated with AILRSE across 12 countries spanning six continents. We investigate the role of AI attitudes, usage of AI tools, and sociodemographic factors to better understand the individual-level factors influencing AI learning self-efficacy. In doing so, our study introduces a new measure that assesses individuals' self-efficacy in learning AI, incorporates motivational factors absent from existing AI scales, and demonstrates its applicability across diverse contexts using large-scale cross-national samples. These unique data enable us to explore cross-national patterns and predictors of AILRSE at a global level. As research on human–computer interaction has gained importance during the recent years of rapid advances in AI technologies, it is essential to understand how people from different backgrounds adopt AI tools.

1.1. *Learning AI in the age of acceleration*

AI technologies are changing the ways in which we work and manage daily tasks. Consequently, the global demand for AI skills is rising. Acquiring such skills is becoming a necessity, not only for experts in certain professions but for virtually everyone. AI skills include a practical capability to use a specific AI-powered tool or product as well as abilities such as solving problems with AI, collaborating with AI or with other humans through AI, and understanding the ethical and societal implications of AI use (Chee et al., 2024).

Acquiring AI skills is crucial for using AI effectively and safely and for being able to recognize misinformation and biases (Rusandi et al., 2023; Saeidnia et al., 2025; Suriano et al., 2025). It also increases competitiveness in the job market (Cedefop, 2025; Chuang et al., 2024). Besson et al. (2024) argued that the successful employment of AI and its economic impact will largely depend on the quality and development of AI-related education and training. It is estimated that a significant number of employees will have to reskill or upskill to meet the demands of the AI-transformed job market (Berg et al., 2023; Jaiswal et al., 2023). A recent international survey found that 71 % of business leaders would prioritize a candidate's AI skills over their experience when making hiring decisions, while 66 % would not recruit an applicant lacking AI skills (Microsoft & Linkedin, 2024). In other words, knowing how to use AI is becoming a basic skill of the 21st century (Steinbauer et al., 2021).

Empirical evidence shows that people with technical skills are more likely to adopt smart technologies (Alshammari, 2024; Matsepe & Van der Lingen, 2022). According to Georgieff and Hyee (2022), high-skilled workers are in a more advantaged position because they are usually already exposed to digital technologies and are more likely to receive necessary AI training. However, in some job settings, less-experienced and lower-skilled workers have gained more benefits from AI tools. A study on customer support agents found that with the help of AI, those with the least experience and weakest skillsets improved the speed and quality of their work to the level of experienced colleagues, whereas high-skilled workers showed only small improvements or even a decrease in quality (Brynjolfsson et al., 2025). This effect, however, may apply only to specific tasks.

Learning how to use AI could become one of the biggest dividing factors societally. Digital divides in AI could mean that those who have access to such tools, take the opportunity, and start learning how to use them are the ones who will receive the greatest benefits from AI (Bentley et al., 2024; Van Dijk, 2020). While low-skilled individuals may experience more notable and immediate gains in certain settings, skilled and technology-ready users also benefit, especially when they continue developing advanced ways of applying AI. Ensuring that AI benefits are distributed evenly requires fostering skills across all groups. Thus, mastering AI tools to increase productivity, quality, and innovation remains central.

Global perspectives on AI use are currently needed due to rapid diffusion of different AI solutions across societies. Earlier research has employed technology acceptance models, such as The Unified Theory of Acceptance and Use of Technology (UTAUT, Venkatesh et al., 2003). Findings of studies over the recent years show that especially positive attitudes toward AI explain the use of smart technologies (Dwivedi et al., 2019). Technology acceptance perspective does not directly address an individual's perceived capability to learn how to use AI effectively. It is notable that a recent large-scale study by Ravšelj et al. (2025) shows major variation in students' perceptions, competences, and emotional reactions to generative AI tools across countries and demographic groups. These findings point to the direction that approaches complementing technology acceptance models would be needed.

1.2. *Conceptualizing AI learning readiness self-efficacy*

AILRSE refers to an individual's belief in their ability to learn and effectively utilize new AI technologies in daily life. This perspective builds on the theory of self-efficacy, which emphasizes how capable individuals perceive themselves to be in carrying out tasks to achieve desired outcomes (Bandura, 1997). Prior studies of technological self-efficacy have focused on computer-use self-efficacy (Compeau & Higgins, 1995), internet-use self-efficacy (Eastin & LaRose, 2000), and robot-use self-efficacy (Latikka et al., 2019). These studies assessed individuals' confidence in understanding how technology works, in using different applications, and in applying this knowledge when needed (Igbaria & Iivari, 1995; Turja et al., 2019). Self-efficacy in technology use thus encompasses not only knowledge but also the perceived ability to use technology in everyday life for practical purposes, such as solving problems (Tsai et al., 2021), as well as the ability to adopt and learn to use technologies independently or with help (Holden & Rada, 2011). Because AI differs from prior technologies, there is a need to create a scale that specifically focuses on self-efficacy in learning to use AI. With its emphasis on learning, AILRSE captures how confident individuals feel in their ability to master AI technologies, regardless of previous experience.

Currently, a range of scales exists to assess factors influencing interactions between humans and AI. In a recent systematic review, Lintner (2024) identified 16 different AI literacy scales developed from diverse perspectives, most of which were adapted from existing technology acceptance or digital literacy frameworks. These scales focused mostly on attitudes, skills, and knowledge rather than self-efficacy and were developed for educational contexts. Lintner (2024) also noted that many of these studies lacked methodological rigor, and none tested cross-cultural validity. Notable examples include Grassini's (2024) Perceived Artificial Intelligence scale (PAILQ-6) and Wang et al., (2023) Artificial Intelligence Literacy Scale (AILS), both of which measure the abilities and competencies required for effective AI use. Other scales emphasize attitudes toward AI, such as Schepman & Rodway, (2023) General Attitudes towards Artificial Intelligence scale (GAAIS), which captures both positive and negative attitudes toward AI. Furthermore, Yilmaz et al., (2024) Generative Artificial Intelligence Acceptance Scale focuses on students' expectancies as well as the facilitating conditions and social influences surrounding generative artificial intelligence use. Some measures address specific aspects of AI proliferation. For example, Wang and Wang's (2022) Artificial Intelligence Anxiety Scale (AIAS) focuses explicitly on the anxieties related to AI in different domains of life.

There are few existing scales that assess AI-related perceptions from a self-efficacy perspective. Morales-García et al., (2024) adapted the widely used General Self-Efficacy Scale into the General Self-Efficacy Scale for use with Artificial Intelligence (GSE-6AI), validating it in an academic setting. Ramazanoglu and Akın (2025) incorporated technology self-efficacy as one dimension of their Readiness for Artificial Intelligence Application Scale (RAIS), developed to assess teachers' preparedness to apply AI in teaching. Other measures apply the self-efficacy concept specifically to student populations, such as Chiu et al.'s (2025) Student AI Competency Self-Efficacy Scale (SAICS), which focuses on students' skills and competencies for adopting AI in learning.

Taken together, these self-efficacy-based AI scales are mostly designed for educational contexts and specific populations, which limits their applicability to large-scale, cross-national research with the general population. Moreover, many existing scales are lengthy and emphasize skills and knowledge, making them less practical for studying AI use and impacts at scale. This highlights the need for a brief tool suitable for diverse samples and contexts. Applying a self-efficacy perspective also makes a theoretical difference to the existing scales focusing on knowledge and literacy about AI, attitudes toward AI, or broad dispositions toward new technologies (technology readiness). Although AILRSE is related to constructs like AI literacy, attitudes, and readiness, its components are not reducible to them. Instead, AILRSE complements these concepts by assessing individuals' perceived capability to effectively learn and apply AI tools in practice.

1.3. Objectives and contributions

This cross-national study utilizes data from four research projects covering cross-national data from six continents and 12 countries (Australia, Brazil, Finland, France, Germany, Ireland, Italy, Japan, Poland, Portugal, South Africa, and the United States). A cross-national perspective is essential because AI adoption, digital skills, and attitudes toward emerging technologies vary considerably across cultural, economic, and policy contexts (Khan et al., 2024; Ravšelj et al., 2025). Comparing countries enables us to test whether the AILRSE construct is measured equivalently across diverse settings and to identify both global patterns and country-specific differences.

Our selection of 12 countries provides broad coverage of six continents and a wide range of cultural, economic, and technological contexts. This diversity is crucial for testing the cross-cultural validity of the AILRSE-5 and for identifying both universal and context-specific patterns in AI learning readiness. The countries were chosen to represent distinct cultural zones of the world (Inglehart & Oyserman, 2004; Inglehart & Welzel, 2005; World Values Survey, 2023). By including countries that differ in AI readiness rankings, digital infrastructure, educational systems, and policy emphasis on AI adoption (Pramanik et al., 2024; Rigley et al., 2024), we can assess whether individual-level predictors of AI learning readiness are consistent across contexts and explore which cultural, economic, or policy factors may drive differences.

The aims of this article are as follows:

1. To validate a concise five-item AILRSE-5 and establish its measurement invariance across countries, within-country samples, and over time.
2. To investigate cross-national patterns and individual-level predictors associated with AILRSE, offering insights into how demographic, attitudinal, and behavioral factors relate to AI learning readiness self-efficacy globally.

The study responds to the urgent need for cross-national evidence on factors influencing AI adoption. We provide not only a new, robust measurement tool but also findings that underscore self-efficacy as a central concept in AI use. Motivation to learn emerging intelligent technologies will likely remain a critical factor for years to come.

2. Methods

2.1. Samples and procedure

We collected 17 samples from 12 countries between 2024 and 2025 as part of four research projects. In total, the samples comprised 20,173 observations. The Self & Technology (SelfTech) project included data from 12 countries. Additional surveys were conducted in Finland: Gambling in the Digital Age (GDA), Social Media at Work (WorkSome), and AI Disruption at Work (WorkAI). Two surveys (SelfTech & GDA) targeted adults aged 18–75, while WorkSome and WorkAI focused on working populations aged 18–65. Sample characteristics and collection periods are presented in Table 1.

The samples were evaluated by comparing their demographic compositions in each country using available census data and analytical tools. These comparisons showed that the European samples closely mirrored their target populations in terms of gender, age, and geographical distribution, based on population statistics from the European Union and Statistics Finland (Heiskari et al., 2025; Oksa et al., 2021; Oksanen et al., 2022). For global samples, those from Brazil and South Africa were somewhat biased toward participants with higher education levels and better access to digital technologies. In contrast, samples from the United States, Australia, and Japan were closely aligned with census age, gender, and education.

All projects were led by the first author. Research groups designed the surveys, which were focused on social media at work, self and technologies, gambling in the digital age, and AI disruption at work. All surveys included some measures on technology use and were designed to take, on average, 15 min to complete. Multinational surveys were created in English and translated into the official languages of the target countries by professional native speakers. Specifically, the survey was administered in English (Australia, Ireland, South Africa, the United States), European Portuguese (Portugal), Brazilian Portuguese (Brazil), French (France), German (Germany), Finnish (Finland), Italian (Italy), Japanese (Japan), and Polish (Poland). A rigorous back-translation procedure was followed to improve the quality of the translations. Surveys were also checked for cross-language consistency by professionals and multilingual team members.

Most data were collected by Norstat, a European provider of online research panels, while the global extension of the SelfTech project was conducted through Dynata, a global online panel provider. All surveys were administered online.

Each project received ethical approval from the relevant ethical review board, which confirmed that there were no ethical concerns regarding the surveys or data collection procedures. In line with established ethical guidelines, informed consent was obtained from all participants prior to data collection. Participants were informed about the general aims of each study, and participation was voluntary.

2.2. AI learning readiness self-efficacy (AILRSE-5)

The AILRSE-5 was developed by the first, the third, and the last author as part of the WorkAI and SelfTech projects. The scale measures individuals' confidence in their ability to learn and adapt to AI-related technologies in work and daily life. Item development drew on established technology self-efficacy frameworks and scales (Igbaria & Iivari, 1995; Tsai et al., 2021; Turja et al., 2019), with wording adapted to explicitly reference AI technologies. At the conceptualization stage, several formulations for items were considered based on content validity, theoretical coverage of core self-efficacy components, and feasibility constraints associated with administering short scales in large-scale survey designs. As a result, the scale was intentionally constructed as a concise short form rather than empirically reduced from a large initial item bank. We originally tested the scale in the WorkAI project, but as the scale performed well, we continued to conduct cross-national surveys without replacing items.

Table 1
Sample characteristics.

Sample	Language	Collection time	N	% women	Mean age (SD)	% univ. educ.	% works
1 Australia – SelfTech	English	10/2024	1487	52.1	46.0 (15.2)	33.69	65.43
2 Brazil – SelfTech	Portug. (BR)	10/2024	1512	53.6	40.5 (14.7)	36.90	76.92
3 Finland – SelfTech	Finnish	10–11/2024	924	50.3	51.5 (15.7)	28.46	51.46
4 France – SelfTech	French	10–11/2024	827	53.3	53.2 (14.4)	34.86	56.42
5 Germany – SelfTech	German	10–11/2024	736	47.2	53.7 (14.2)	30.30	54.89
6 Ireland – SelfTech	English	10–11/2024	468	46.8	53.2 (14.1)	52.99	61.75
7 Italy – SelfTech	Italian	10–11/2024	947	51.1	52.7 (14.1)	38.33	57.44
8 Japan – SelfTech	Japanese	10/2024	1569	50.9	48.8 (16.2)	44.04	58.89
9 Poland – SelfTech	Polish	10–11/2024	731	50.3	52.5 (14.6)	60.88	60.60
10 Portugal – SelfTech	Portug. (POR)	10–11/2024	1522	51.4	46.2 (14.9)	31.80	71.09
11 South Africa – SelfTech	English	10–11/2024	1530	50.8	38.0 (14.8)	16.01	63.99
12 United States – SelfTech	English	10–11/2024	1543	52.4	45.8 (15.9)	37.14	55.35
13 Finland – GDA	Finnish	4–5/2025	790	49.4	54.9 (15.2)	43.60	50.57
14 Finland – GDA drop-in	Finnish	4/2025	1023	51.1	46.8 (16.3)	33.72	54.35
15 Finland – WorkSome	Finnish	3–4/2025	775	44.0	51.3 (11.1)	52.00	84.05
16 Finland – WorkAI, T1	Finnish	8–9/2024	2109	49.5	42.6 (11.9)	44.87	100
17 Finland – WorkAI, T2	Finnish	2–4/2025	1680	47.4	44.3 (11.7)	44.87	93.33

Table 2 presents a formulation of each item. An initial larger pool of items was shortened during the process of designing the surveys, resulting in a five-item scale. The short format ensures that the measure can be efficiently integrated into surveys across diverse populations and research settings while still capturing core aspects of AI learning and self-efficacy. The items cover confidence in understanding how AI works, the ability to apply AI in practice, and general self-belief in one's capacity to use AI for problem solving. Responses were measured on a seven-point scale, with response options ranging from 1 (*strongly disagree*) to 7 (*strongly agree*). Higher scores indicate greater AILRSE.

2.3. Other measures

Positive AI attitude was measured with a four-item version of the positivity dimension of the GAAIS (Schepman & Rodway, 2020, 2023). Items included statements such as "Much of society will benefit from a future full of Artificial Intelligence." Response options ranged from 1 (*strongly disagree*) to 7 (*strongly agree*). Higher scores indicate more positive attitudes toward AI. Reliability was high across samples, with McDonald's omegas (ω) ranging from 0.94 to 0.97.

We measured the use of AI tools by focusing on tools designed to generate written text, such as ChatGPT or Copilot. We focused specifically on text-to-text generators, which are the most widely adopted generative AI tools globally. All participants were asked the same introductory question about how often they use these tools, with response options ranging from "never" to "daily use." For analysis, we created a binary variable indicating weekly use (0 = less than once per week, 1 = at least once per week).

Socio-demographic variables utilized in the study included age, gender, education, and occupational position. Age was used as a continuous variable. Gender was assessed with the response options "woman," "man," and "other." For statistical modeling, we created a binary variable representing women (coded as 1) versus men and participants of other genders (coded as 0). Because the number of participants identifying with genders other than male or female was relatively small, they were combined with men in the reference category.

Table 2
Item formulation for AILRSE-5.

Item No.	Item Formulation	Adapted/Self-developed
1	I'm confident in my ability to understand how new AI technologies work.	Igbaria and Iivari (1995)
2	I'm confident in my ability to learn how to use new AI technologies if necessary.	Igbaria and Iivari (1995), Turja et al. (2019)
3	I'm confident in my ability to learn how to apply new AI technologies in my daily life.	Tsai et al. (2021)
4	I'm confident in my ability to learn how to use new AI technologies to solve a problem.	Tsai et al. (2021)
5	I'm confident in my ability to learn how to use new AI technologies independently.	Self-developed

Note. AILRSE = AI learning readiness self-efficacy scale. The scale for all the items ranged from 1 (*strongly disagree*) to 7 (*strongly agree*). References are provided for items adapted from earlier measures. Item No. = item number.

Education was assessed in each survey using country-specific classifications that followed national standards. For comparability across samples, we created a binary variable indicating (at least a bachelor's degree) in each country (0 = no university education, 1 = university education). Occupational position was assessed in most surveys using a similar classification. For statistical analyses, we created a binary variable indicating employment status (0 = not working, 1 = working). The "working" category included participants in paid employment or self-employed/entrepreneurial roles. The "not working" category included students, unemployed individuals (both seeking and not seeking employment), retirees, permanently sick or disabled individuals, and those engaged in housework or caregiving.

2.4. Statistical techniques

We used confirmatory factor analysis (CFA) to assess the construct validity of the scale in all our samples. Then, we used multiple-group CFA to evaluate measurement invariance in 12 countries and cross-sectionally across five different study samples. Finally, we used multiple-group CFA to analyze longitudinal measurement invariance at two time points in one sample. We conducted these analyses in R (version 4.4.3) using *lavaan* (0.6–19), *psych* (2.4.12), and *semTools* (0.5–6).

We tested four levels of invariance, adding constraints incrementally. Configural invariance establishes that the basic factor structure is consistent across countries. For metric invariance, the item factor loadings were constrained to be equal across countries, ensuring that the relationships between items and the latent construct were consistent across countries. For scalar invariance, the item loadings and intercepts were constrained to be equal across countries, ensuring that the latent construct was measured equivalently across countries. Finally, for strict invariance, the item residual variances were also constrained to be equal, establishing that the measurement error was equivalent across countries.

We used several indices to evaluate model fit. As the Chi-square test is sensitive to sample size (Cheung & Rensvold, 2002), we also used the following recommended indices (Putnick & Bornstein, 2016) to evaluate model fit: the Comparative Fit Index (CFI), Tucker–Lewis Index (TLI), root mean squared error of approximation (RMSEA), and standardized root mean squared residual (SRMR). For the CFI and TLI, values over 0.95 were considered a good fit, while the cut-off values for RMSEA and SRMR were 0.06 and 0.08, respectively (Hu & Bentler, 1999). For differences between models, acceptable thresholds were defined as ΔCFI and ΔTLI ≥ -0.01 and ΔRMSEA ≤ 0.015 (Chen, 2007). Because RMSEA is sensitive to large samples and many groups (Rutkowski & Svetina, 2014), we used a more lenient RMSEA cutoff value of 0.10 and ΔRMSEA value of 0.03 for metric invariance, as suggested by Rutkowski & Svetina, (2014).

Prior to model estimation, we tested assumptions for structural equation modeling (SEM). Multivariate normality was tested using Mardia's test, and multicollinearity was examined with variance inflation factors (VIFs) and tolerance values. We used robust maximum likelihood estimation with the Yuan–Bentler correction, which provides robust fit statistics and may slightly increase RMSEA and χ^2 values due to scaling effects. We measured internal consistency using Cronbach's alpha, McDonald's omega, and the composite reliability index (CR), with values ≥ 0.70 considered acceptable. Convergent validity was evaluated using the average variance extracted (AVE), with values ≥ 0.50 indicating adequate convergent validity.

The last part of the analysis focused on associations of AILRSE and socio-demographic factors, positive AI attitude, and the use of AI tools. These analyses were conducted with Stata18 using the *regress* and *xtreg* commands. Homoscedasticity was assessed, and robust Huber–White standard errors were applied. Multicollinearity was examined using VIFs, and no issues were detected. Models report standardized (β) coefficients and statistical significance. Longitudinal analyses were conducted with the WorkAI survey data using both random and fixed effects models.

3. Results

The first part of the analysis involved CFA conducted separately for each sample. Table 3 reports descriptive statistics, along with reliability and validity metrics for each sample. Country-level means ranged from 19.3 (Japan) to 28.7 (Brazil) on a scale of 5–35, indicating that, in general, participants reported moderate-to-high AI learning readiness self-efficacy across samples. Standard deviations (6.0–8.0) suggested moderate to high within-sample variability, indicating that the measure captures sufficient variability to allow reliable cross-national and individual-level comparisons. In addition, internal consistency was high across datasets (Cronbach's α and McDonald's ω ≥ 0.94; CR ≥ 0.94), and AVE values were between 0.75 and 0.87, indicating strong item interrelatedness and convergent validity for the AILRSE-5 scale.

In the SelfTech dataset, Mardia's test indicated multivariate nonnormality, and some item intercorrelations were high (0.77–0.88). Therefore, CFA used robust maximum likelihood estimation with the Yuan–Bentler correction. The hypothesized one-factor model showed good fit in most samples: CFI ranged from 0.971 to 0.998, and TLI exceeded 0.95 in all but Brazil (0.942). RMSEA varied more widely (0.046–0.163), with elevated values in some samples (e.g., Brazil, Ireland) that were reduced to acceptable levels after allowing residual correlations between Items 1 and 2. SRMR values were consistently low (0.006–0.025). Overall, the scale demonstrated good model fit, with RMSEA variability likely reflecting sample-specific characteristics or sensitivity to large samples.

In the second stage, we tested the model's cross-cultural performance using multiple-group CFA across 12 countries. As shown in Table 4, the results supported scalar invariance. Although the χ^2 test was significant at all invariance levels, this is expected with large samples. CFI was 0.989 at the configural level, decreasing slightly to 0.988 (ΔCFI = −0.001) at the metric level and to 0.979 (ΔCFI = −0.009) at the scalar level. Constraining residual variances further reduced CFI to 0.958 (ΔCFI = −0.021), indicating that strict invariance was not achieved. RMSEA at the configural level was 0.109 (90 % CI [0.098, 0.119]), a value considered acceptable given the large sample, robust estimation, and the relaxed 0.10 cutoff for multi-group models. RMSEA decreased to 0.087 (90 % CI [0.087, 0.094]) at the metric level, suggesting improved model fit with equal loadings, and increased slightly to 0.097 (90 % CI [0.092, 0.102]) at the scalar level, remaining under the 0.10 threshold. SRMR values were below 0.08 at all stages. Overall, the invariance results indicate that the scale operates equivalently across countries at the scalar level, with RMSEA more stable in the multi-group model than in single-country models, likely reflecting a more parsimonious overall structure and reduced overfitting.

The third analysis examined measurement invariance across five Finnish samples. As shown in Table 4, χ^2 difference tests were significant in all nested models, but CFI changes remained below the 0.01 threshold (configural–metric ΔCFI = −0.001; metric–scalar ΔCFI = −0.006; scalar–strict ΔCFI = −0.007), supporting strict invariance. RMSEA values were generally lower than in the cross-country analysis, suggesting a more consistent factor structure within a single cultural context. Starting at 0.073 (90 % CI [0.058, 0.089]) at the configural level, RMSEA decreased to 0.060 (90 % CI [0.050, 0.071]) at the metric level, rising to 0.074 (90 % CI [0.066, 0.082]) at the scalar level and 0.083 (90 % CI [0.075, 0.091]) at the strict level. All RMSEA values were within acceptable bounds for multi-sample comparisons, with slightly higher values over 0.06 considered tolerable given the robust estimation method and moderate group sizes. SRMR values were below 0.08 across all levels. Overall, the findings indicate that the scale demonstrates strict invariance across Finnish samples, with better fit stability than in the international comparison.

Table 3
AILRSE-5 scale metrics.

Sample	Mean (SD)	α	ω	CR	AVE	CFA χ^2/df	CFI	TLI	RMSEA (90 % CI)	SRMR
1 Australia – SelfTech	21.8 (7.05)	0.95	0.95	0.954	0.806	10.514 (5)	0.998	0.996	0.045 (0.000–0.083)	0.008
2 Brazil – SelfTech	28.7 (6.22)	0.94	0.94	0.937	0.748	55.201 (5)	0.971	0.942	0.158 (0.122–0.196)	0.025
3 Finland – SelfTech	21.6 (7.16)	0.95	0.96	0.955	0.812	34.646 (5)	0.988	0.977	0.116 (0.081–0.154)	0.009
4 France – SelfTech	20.7 (7.95)	0.97	0.97	0.97	0.867	59.341 (5)	0.981	0.962	0.163 (0.127–0.201)	0.014
5 Germany – SelfTech	22.6 (7.70)	0.96	0.97	0.966	0.851	12.040 (5)	0.997	0.994	0.066 (0.017–0.115)	0.008
6 Ireland – SelfTech	21.7 (7.18)	0.95	0.95	0.952	0.804	21.373 (5)	0.987	0.973	0.122 (0.072–0.178)	0.020
7 Italy – SelfTech	22.3 (7.49)	0.97	0.97	0.966	0.852	12.452 (5)	0.997	0.993	0.064 (0.019–0.110)	0.008
8 Japan – SelfTech	19.3 (6.76)	0.96	0.96	0.965	0.845	43.236 (5)	0.992	0.983	0.101 (0.075–0.130)	0.011
9 Poland – SelfTech	23.0 (6.91)	0.95	0.96	0.955	0.811	16.868 (5)	0.992	0.984	0.096 (0.048–0.148)	0.012
10 Portugal – SelfTech	25.2 (6.04)	0.96	0.96	0.958	0.822	24.648 (5)	0.994	0.987	0.084 (0.053–0.118)	0.010
11 South Africa – SelfTech	28.1 (6.54)	0.94	0.94	0.94	0.755	52.554 (5)	0.981	0.962	0.130 (0.100–0.163)	0.019
12 United States – SelfTech	23.2 (7.49)	0.95	0.95	0.95	0.792	27.833 (5)	0.991	0.983	0.094 (0.062–0.129)	0.014
13 Finland – GDA	21.0 (7.72)	0.97	0.97	0.967	0.855	10.725 (5)	0.997	0.995	0.057 (0.000–0.104)	0.007
14 Finland – GDA drop-in	21.6 (7.66)	0.96	0.96	0.964	0.843	10.343 (5)	0.998	0.997	0.046 (0.000–0.085)	0.006
15 Finland – WorkSome	22.2 (7.33)	0.96	0.97	0.964	0.843	14.588 (5)	0.996	0.992	0.071 (0.030–0.114)	0.007
16 Finland – WorkAI, T1	23.1 (6.70)	0.95	0.95	0.945	0.774	25.850 (5)	0.996	0.992	0.065 (0.042–0.091)	0.007
17 Finland – WorkAI, T2	22.8 (6.76)	0.95	0.95	0.95	0.796	29.989 (5)	0.994	0.989	0.078 (0.053–0.107)	0.010

Table 4
Invariance test models.

Model	χ^2	df	$\Delta\chi^2$	p ($\Delta\chi^2$)	CFI	ΔCFI	RMSEA (90 % CI)	ΔRMSEA	SRMR
1 SelfTech									
configural	374.987	60			0.989		0.109 (0.098–0.119)		0.012
metric	577.534	104	133.97	<0.001	0.988	−0.001	0.087 (0.080–0.094)	−0.022	0.027
scalar	1131.720	148	753.77	<0.001	0.979	−0.009	0.097 (0.092–0.102)	0.010	0.040
strict	1586.580	203	440.01	<0.001	0.958	−0.021	0.116 (0.111–0.122)	0.019	0.042
partial strict, item1 free	1318.880	192	256.99	<0.001	0.967	−0.012	0.106 (0.101–0.112)	0.009	0.041
2 Finland – cross-sectional									
configural	96.513	25			0.995		0.073 (0.058–0.089)		0.006
metric	145.955	41	38.159	0.001	0.995	−0.001	0.060 (0.050–0.071)	−0.013	0.021
scalar	298.394	57	189.946	<0.001	0.989	−0.006	0.074 (0.066–0.082)	0.014	0.030
strict	392.923	77	98.552	<0.001	0.982	−0.007	0.083 (0.075–0.091)	0.009	0.030
3 Finland – longitudinal									
configural	96.254	29			0.994		0.047 (0.037–0.058)		0.016
metric	103.852	33	2.72	0.606	0.994	0.000	0.044 (0.035–0.054)	−0.003	0.017
scalar	116.444	38	11.20	0.048	0.994	0.000	0.042 (0.034–0.051)	−0.002	0.018
strict	113.274	43	3.13	0.680	0.994	0.000	0.039 (0.030–0.048)	−0.003	0.019

In the fourth part, we examined longitudinal measurement invariance using Finnish data at two time points to assess the scale's temporal stability. The χ^2 difference test was non-significant from the configural to metric levels (p ($\Delta\chi^2$) = 0.606) and significant when moving to the scalar level, but χ^2 is known to be sensitive to large samples. Other indices indicated excellent fit across all invariance levels. CFI remained stable at 0.994 (ΔCFI <0.001), and RMSEA values decreased slightly at each step from 0.047 (90 % CI [0.037, 0.058]) at the configural level to 0.044, 0.042, and 0.039 at the metric, scalar, and strict levels, respectively. This suggests that those added constraints improved model parsimony without compromising fit. SRMR values were consistently below 0.02 across all levels. Overall, the results support strict longitudinal invariance, indicating that the scale measures the same construct equivalently across time.

The final part of the analysis focused on the predictors of AILRSE. Table 5 presents standardized beta coefficients from linear regression models predicting AILRSE across all samples. Across countries, younger age was consistently associated with higher AILRSE (β = −0.04 to −0.16, mostly $p < .001$), and AI positivity was the strongest predictor in every model (β = 0.38 to 0.61, all p < .001). Text-to-text generator use was a significant positive predictor in all SelfTech samples (β = 0.07 to 0.26, $p < .05$), with the largest effect observed in Japan. Gender effects were generally small and inconsistent: In some countries (e.g., France, Japan), women reported slightly lower AILRSE than men, whereas in other countries the differences were not statistically significant. University education and employment status showed modest positive associations in certain contexts, although the effects varied by country. In the Finnish-only surveys (GDA, WorkSome, WorkAI), younger age, higher education, and AI positivity (when included) were consistently linked to higher AILRSE. Our longitudinal analysis of WorkAI further confirmed these findings in random-effects regression models. In fixed effects models, we found within-person effects of positive AI attitudes on AILRSE ($p < .001$). We also found a smaller positive within-person effect of weekly text-to-text generator use on AILRSE ($p = .024$).

4. Discussion

Willingness and ability to learn how to use new AI tools are increasingly important in today's technology-driven society. Robust cross-national evidence on these psychological aspects, however, has been limited. In this study, we first aimed to validate the five-item AILRSE-5 across 12 countries, using both cross-sectional and longitudinal samples and secondly, we aimed to examine how individual factors such as positive AI attitudes, usage of AI tools, and sociodemographic factors associate with AI learning self-efficacy.

CFA results supported a one-factor structure with high internal consistency in all samples. Scalar invariance was achieved across countries, and strict invariance was supported in Finnish cross-sectional and longitudinal data, confirming that the scale functions equivalently across diverse contexts and over time. Regression analyses identified positive AI attitudes as the strongest predictor of AILRSE in all countries, followed by younger age and more frequent use of text-to-text AI tools.

Table 5
Linear regression models explaining AILRSE (standardized beta regression coefficients, statistical significances and model statistics).

Model	Age	Female	Univ. educ.	Works	AI positivity	Text gen. use	Model n	Adj. R2
AUS – SelfTech	−0.15***	−0.07**	0.04*	0.07**	0.48***	0.16***	1487	0.43
BRA – SelfTech	−0.08**	0.02	0.03	0.03	0.59***	0.14***	1512	0.45
FIN – SelfTech	−0.16***	−0.05	0.05	0.08**	0.44***	0.12***	924	0.32
FRA – SelfTech	−0.13***	−0.09***	0.09**	0.07*	0.52***	0.07**	827	0.41
GER – SelfTech	−0.04	−0.06*	0.06*	0.10**	0.61***	0.07**	736	0.46
IRE – SelfTech	−0.16***	−0.01	0.01	0.07	0.51***	0.09*	468	0.34
ITA – SelfTech	−0.07*	−0.09**	0.04	0.06*	0.55***	0.12***	947	0.40
JPA – SelfTech	−0.12***	−0.09***	0.05*	0.06**	0.38***	0.26***	1569	0.35
POL – SelfTech	−0.09**	−0.02	0.06	0.03	0.50***	0.10***	731	0.31
POR – SelfTech	−0.07**	−0.03	−0.00	0.05*	0.51***	0.13***	1522	0.34
ZAF – SelfTech	−0.14***	−0.02	−0.01	0.05*	0.59***	0.08***	1530	0.44
USA – SelfTech	−0.10***	−0.03	0.03	0.05*	0.48***	0.16***	1543	0.36
FIN – GDA	−0.24***	−0.14***	0.17***	0.06	–	–	788	0.15
FIN – GDA drop-in	−0.27***	−0.07*	0.21***	0.08**	–	–	1023	0.14
FIN – WorkSome	−0.09**	−0.02	0.10**	–	0.43***	0.15***	648	0.31
FIN – WorkAI–T1	−0.09***	−0.03	0.09***	–	0.46***	0.14***	2109	0.33

Note. Statistical significance levels indicated by * $p < .05$, ** $p < .01$, *** $p < .001$.

Associations with gender, education, and occupational position were small and inconsistent across contexts.

4.1. Theoretical and practical implications

These findings contribute to the growing body of literature on AI self-efficacy. AILRSE-5 is a short and practical measure for cross-national and longitudinal research. While most previous scales have focused on educational context, AILRSE offers a general measure to examine AI learning self-efficacy in wider populations. Scalar invariance across culturally diverse countries highlights its potential as a tool for global benchmarking and meta-analyses.

AILRSE scale fills the gap not addressed by existing measures. AI literacy and competence scales target AI knowledge and skill-based competence, while AILRSE measures individuals' belief in their capability to learn to use and utilize AI technologies in everyday life. The self-efficacy framework is especially useful, as it links belief and behavior (Bandura, 1997; Li et al., 2024), and aligns with prior work emphasizing the role of attitudes in technology acceptance and use (Kulviwat et al., 2014; Venkatesh et al., 2003).

From a practical standpoint, research on AI self-efficacy is crucial given the rapid pace of technological development. Our results provide robust cross-national evidence that AILRSE is a valid construct. As a short measure, AILRSE-5 can be widely applied in research, education, and training, yet its relevance extends beyond educational settings. Developing proficiency in using AI is becoming a necessity across various contexts, particularly in the workplace (Cedefop, 2025; Chuang et al., 2024). Self-efficacy perspective on AI expands earlier discussions related to technology acceptance that have shown especially the relevance of attitudes toward technologies (Dwivedi et al., 2019). Our findings on association of positive AI attitudes and AILRSE show that it is meaningful to integrate AILRSE into models explaining AI use. Also, investigating both AILRSE and attitudes towards AI helps to identify specific demographic groups that may experience barriers in AI adoption, which has practical relevance.

Although predictors of AILRSE were generally consistent across countries, we found some differences. For example, in Australia, France, Italy, and Poland women reported lower AILRSE. These differences are likely to reflect roles in society, but the effects are rather modest. Also, in Finland we can see that there is no gender difference in samples focusing on workers. Similarly, there are other minor differences in the role of education across datasets, which is not surprising considering the societal and cultural differences. Our findings suggest that cultural, occupational, and technological environments play a part in shaping how individuals evaluate their AI learning readiness.

Assessing individuals' confidence and readiness to learn to use AI can help identify psychological and contextual barriers to learning. This understanding can inform targeted strategies to encourage people to develop skills enabling them to use AI tools efficiently, safely, and in ways that benefit their development and well-being. From a policy perspective, AILRSE could be incorporated into national or organizational AI initiatives to identify groups needing additional support. It could be also used when designing interventions to reduce emerging AI divides. The scale can also guide the development of training programs by highlighting which groups have lower perceived AI learning readiness and may benefit from mentoring or tailored support. Because the scale demonstrated strict invariance over time in the longitudinal data, it is suitable for monitoring individual or population-level changes in AI learning self-efficacy. This allows policymakers, educators, and organizations to track developmental trajectories and evaluate the impact of training or inclusion-focused policies. Future research could continue analyzing how AILRSE interacts with specific training designs, workplace changes, or societal efforts to improve digital inclusion.

4.2. Strengths and limitations

A key strength of this study is the development and validation of the AILRSE-5 scale using large-scale cross-national survey data. The inclusion of both cross-sectional and longitudinal analyses provides robust evidence for the stability and reliability of the scale over time. Demonstrating the cross-cultural validity and usability of the scale across 12 countries significantly enhances the contribution of this study.

Our study has some limitations that should be acknowledged. Self-reported measures may be subject to biases, for example, social desirability or recall errors. Other limitations are related to the samples. Collecting fully population-representative samples from developing countries is challenging, and online surveys often reach more digitally active individuals. Our samples from Brazil and South Africa were biased toward participants with higher education and better access to digital technologies. These factors might have affected some of our results in these countries. These samples also contain a larger proportion of younger respondents, which aligns with the younger demographic structure of these societies compared to several of the other countries in our dataset.

Although measurement invariance was largely supported, some country-specific CFAs showed elevated RMSEA values, which could reflect model sensitivity in large datasets or potential cultural variation in item interpretation. Although wording was closely adapted by native speakers, national and cultural differences in familiarity with AI may influence interpretation. Also, it is likely that there are cultural differences in how people interpret not only AI, but learning and mastering AI. Self-efficacy beliefs could also generally vary culturally (Ahn, Usher, & Butz, 2016). Despite this, we consider our findings robust. They were consistent and scalar invariance was supported, and other fit indices indicated good fit.

We did find strict variance in Finnish longitudinal and cross-national samples, but not across 12 countries. Importantly, scalar invariance was supported, meaning that loadings and intercepts were comparable across groups, allowing valid comparisons of latent AILRSE levels. The lack of strict invariance does not compromise the usability of the AILRSE scale, because scalar invariance is sufficient for comparing latent means, and residual variance differences are common in cross-national datasets. Reaching strict invariance in longitudinal data shows however that AILRSE can reliably track individual trajectories over time. This means it has excellent potential for future research.

4.3. Conclusions

This study demonstrates that AILRSE is important in today's digital context and is globally associated with attitudes toward and adoption of AI tools. AILRSE-5 is a brief, robust, and valid instrument for assessing this construct across cultures and over time. It enables research on self-efficacy and related motivational factors in AI adoption and learning. Future studies can examine its predictive value for behavioral (e.g., persistence in learning AI, sustained engagement), cognitive (e.g., perceived autonomy in problem-solving, capacity to integrate AI into tasks), and affective outcomes (e.g., reduced technology-related anxiety). It can also be applied to study longitudinal trajectories with AI as well as the effectiveness of interventions aimed at strengthening AI-related skills and confidence. Additionally, the scale has practical relevance for education, training, and policy, offering a tool for identifying barriers and informing strategies to foster AI readiness in society.

CRediT authorship contribution statement

Atte Oksanen: Writing – review & editing, Writing – original draft, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Teijo Osma:** Writing – review & editing, Writing – original draft, Software, Methodology, Investigation, Formal analysis, Conceptualization. **Moona Heiskari:** Writing – review & editing, Writing – original draft, Methodology, Data curation, Conceptualization. **Anica Cvetkovic:** Writing – review & editing, Writing – original draft. **Eerik Soares Ruokosuo:** Writing – review & editing, Writing – original draft, Data curation. **Mayu Koike:** Writing – review & editing, Writing – original draft, Data curation. **Patrícia Arriaga:** Writing – review & editing, Writing – original draft, Data curation. **Iina Savolainen:** Writing – review & editing, Writing – original draft, Supervision, Resources, Funding acquisition, Data curation, Conceptualization.

Ethical approval

The ethics committee of Tampere region has reviewed the research protocol across multiple project phases and concluded that studies do not pose any ethical issues (decisions 83/2018, 24/2021, 115/2022, 45/2024).

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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