

Article

The SPArKED Instrument: Gathering Validity Evidence for Measuring Digital-Age Lifelong Learning

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Abstract

Introduction: Traditional instruments for measuring lifelong learning of health professionals fail to capture digital-age learning, creating a critical measurement disconnect. To address this gap, we developed a 16-item Self-Pursuits, Aspirations, and Knowledge Endeavors in the Digital Era (SPArKED) instrument. **Methods:** To gather validity evidence for SPArKED, a cross-sectional survey was deployed to health professional students ($n = 558$). The survey questionnaire included: SPArKED, Jefferson scale of lifelong learning for students in health professions, basic psychological needs satisfaction scale, and human-computer trust scale assessing students' trust in generative technology to support lifelong learning. Exploratory factor analysis (EFA) and correlation analysis were performed. **Results:** The EFA of the SPArKED revealed a three-component structure: networked learning, i-learning (individual mastery), and AI-powered learning, together explaining 55% of the total variance. The SPArKED demonstrated good internal consistency ($\alpha = 0.86$) and convergent validity with the Jefferson scale of lifelong learning ($r = 0.75$). The correlations between SPArKED and psychological needs satisfaction scores were moderately high: autonomy ($r = 0.50$), competence ($r = 0.48$), and relatedness ($r = 0.51$). SPArKED had a higher correlation with students' trust in generative technology to support lifelong learning than the Jefferson scale ($r = 0.52$ and $r = 0.32$, respectively). **Conclusions:** Compared to the Jefferson scale, the SPArKED instrument appears to better capture digital-age learning behaviors among students in health professions. By assessing these evolving behaviors in learners, education programs can better guide future health practitioners in developing desired lifelong learning competencies and digital literacies. Future research should gather validity evidence for SPArKED across diverse learner samples and educational stages, informing a critical re-assessment of established instruments in the rapidly evolving learning landscape.



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Keywords: lifelong learning; digital-age learning; measurement; scale development; psychometric

1. Introduction

Rapid digital advancements are creating new paradigms of how younger generations learn and approach learning [1,2]. These generations have never experienced the world without the internet, social media, instant connectivity, and access to information [3]. Their lifelong digital immersion is being further reinforced by the growing integration of digital tools into education [4–7], cultivating reliance and trust in digital technology to facilitate learning beyond formal education [1,8,9]. A key reason to study these generations' learning behaviours is that their developing approach will be crucial for their professional success,

especially since professionals must commit to lifelong learning to remain current and effective. Yet, a recent systematic review [10] revealed substantial variation in how the construct of lifelong learning is conceptually defined, operationalized, and measured across diverse contexts and disciplines. The review identified 18 instruments for measuring lifelong learning in professionals, offering a critical evaluation of their content and measurement properties. The authors concluded that most of the instruments lacked a clear definition and current construct presentation and called for their judicious use in practice [10].

In the context of health professions specifically, lifelong learning is a critical competency for the safe and effective patient care [11–15]. The frequently cited definition of lifelong learning in health professional literature is the one proposed in 2003 by Hojat and colleagues [12]. They defined lifelong learning as “a concept involving a set of self-initiated activities and information-seeking skills that are activated in individuals with a sustained motivation to learn and the ability to recognize their own learning needs.” [12] (p. 434). Based on the definition, these scholars subsequently developed the Jefferson Scale of Physician Lifelong Learning (JeffSPLL) [12,13], which was adapted for use with medical students (JeffSPLL-MS) [14] and students in other health professions (JeffSLL-HPS) [15] (shown in Appendix A). The 2024 systematic review by Verkooijen and colleagues [10] identified the Jefferson scale as the most widely used instrument for measuring lifelong learning in the health professions, with published evidence for content and methodological quality across diverse populations of health practitioners and trainees. Since its development, the Jefferson scale has been used in studies across different geographic regions, including Canada, China, Croatia, Iran, Paraguay, Peru, Portugal, Romania, Taiwan, the Netherlands, the United States, South America, and Uganda [10].

While foundational frameworks in health professional education and practice define lifelong learning as an individual, self-directed attribute characterized by a drive to learn and self-assessment skills [12–15], the digital era necessitates a fundamental reconceptualization. Lifelong learning in the modern era is no longer a purely internal cognitive process; rather, it is a distributed, socio-technical capability [16]. In digitally mediated and AI-supported environments, lifelong learning involves a health practitioner’s ability to critically navigate, evaluate, and co-learn alongside digital technology and within environments deeply embedded with digital tools, telehealth networks, and AI decision support. In this landscape, the locus of learning shifts from the isolated individual to a dynamic interaction between the human learner and digital technology. As such, existing instruments designed to measure lifelong learning must be re-examined to capture how future health professionals learn with technology. To this end, we developed the **S**elf-Pursuits, **A**spirations, and **K**nowledge **E**ndeavors in the **D**igital Era (SPArKED; shown in Table 1) based on established practices in scale development [17] and findings from focus groups we conducted with postsecondary students [1].

Specifically, the focus groups data revealed that students use digital technology for learning because it facilitates experiences of agency, growth, and connection [1], which is in line with the self-determination theory (SDT) framework of basic psychological needs [18,19]. According to SDT, individuals are drawn to activities insofar as they fulfill their needs for autonomy, competence, and relatedness [18,19]. Autonomy is the need to be in control over one’s choices and actions; competence is the need to experience mastery and self-efficacy; and relatedness is the need for belonging and feeling connected. As such, we used the focus-group findings and SDT as a lens in developing and gathering validity evidence for the SPArKED instrument.

The content of the SPArKED items was guided by the framework of digital affordances for learning outlined by Smith and colleagues [4]. The framework delineates four broad categories of digital affordances understood as inherent technology qualities that enable

learning: administering and organizing learning; seeking help and information; creating, sharing and communicating information; and simulating environments for deliberate practice of skills [4]. To evaluate the face validity, clarity, and contextual appropriateness of the draft items, we used think-aloud and verbal probing [17,20] with a purposive sample of students ($n = 4$). This approach helped ensure that the items were interpreted by the target audience as intended, helping refine potentially ambiguous phrasing, and verified the overall comprehensiveness of the items [17,20].

Table 1. Descriptive statistics for the SPArKED items ($n = 558$ students).

Item *	Agree/Strongly Agree, %	Mean (SD)
1. I explore new topics primarily through digital resources.	97%	3.50 (0.57)
2. I engage in online learning even when there are no deadlines or external accountability.	82%	3.13 (0.73)
3. I take advantage of free digital resources to enhance my knowledge and skills.	94%	3.45 (0.62)
4. I always assess the credibility of digital resources I use for self-study.	89%	3.27 (0.69)
5. I leverage digital tools like apps, podcasts, and e-books in my self-paced learning.	81%	3.11 (0.76)
6. I use online tutorials or how-to videos to learn or enhance my skills.	90%	3.30 (0.66)
7. I take advantage of online simulations or interactive tools to practice new skills.	79%	3.09 (0.77)
8. I use online assessment tools like quizzes to gauge my understanding of topics.	84%	3.22 (0.76)
9. I use AI-powered tools like ChatGPT and virtual tutors to assist me in my learning.	81%	3.15 (0.87)
10. I routinely participate in online study groups or peer collaboration platforms.	47%	2.46 (0.99)
11. I seek learning opportunities through social media or professional networks.	71%	2.87 (0.81)
12. I engage in live Q&A sessions or webinars hosted by experts in my field.	50%	2.50 (0.99)
13. I actively contribute to online forums or communities by sharing my knowledge and experiences.	48%	2.42 (1.01)
14. I participate in virtual seminars or conferences related to my professional interests.	59%	2.67 (0.94)
15. I follow social media for new ideas and trends in my field/profession.	84%	3.16 (0.77)
16. I use generative AI tools like ChatGPT to explore and develop my ideas.	75%	3.00 (0.92)

* Items are shown in the order they appeared on the questionnaire. Items were answered on a four-point scale (1-strongly disagree to 4-strongly agree).

The objective of the present study was to gather validity evidence for the SPArKED instrument. Specifically, we examined its psychometric properties and its associations with students' basic psychological needs, their scores on the Jefferson Scale, and trust in generative technology to support their lifelong learning.

2. Methods

2.1. Study Design

To meet the study objective, a quantitative cross-sectional survey design was employed as part of a larger research project investigating lifelong learning of postsecondary students in the digital era. In the project's first phase, a qualitative analysis of focus-group data was conducted to explore students' self-initiated learning practices and perspectives on lifelong learning [1], informing the SPArKED item development. In the present study, a quantitative cross-sectional survey design was selected because the study's objective was to obtain evidence of content and convergent validity for the SPArKED instrument.

Ethical approval was obtained for the larger study from the Research Ethics Board at the University of Alberta (REB #Pro00102091; date of approval: 17 April 2025). The present study was conducted in accordance with the Declaration of Helsinki. Generative AI was not used in this study to assist in study design, data collection, analysis, or interpretation.

2.2. Measures

The survey was developed in Qualtrics^{XM} (version accessed between April 2025 and June 2025). The survey questionnaire included the 16-item SPArKED (shown in Table 1) and the 14-item JeffSLL-HPS [15] (shown in Appendix A). The items on the JeffSLL-HPS assess self-initiated learning activities, information-seeking skills, and professional learning beliefs and motivation. Students were asked to respond to each item using a four-point scale (1-strongly disagree; 4-strongly agree). The same response scale was adopted for the SPArKED items. In this study, the internal consistency values (Cronbach alpha) of SPArKED and JeffSLL-HPS were $\alpha = 0.87$ and $\alpha = 0.86$, respectively.

To measure students' psychological need satisfaction as they continue learning, we employed the psychological need states scale [21] (shown in Appendix A). Satisfaction of each need (autonomy, competence, and relatedness) was assessed via five items, utilizing a 7-point response format (1-strongly disagree; 7-strongly agree). In this study, the internal consistency values (Cronbach alpha) were: $\alpha = 0.75$ for autonomy, $\alpha = 0.85$ for competence, and $\alpha = 0.86$ for relatedness.

Also included in the survey was the 12-item human–computer trust scale (HCTS) [22], an instrument for assessing trust in technology, which has been applied in various contexts and with distinct populations [23]. The HCTS items encompass four attributes: perceived risk associated with technology use; benevolence or perception that technology can act in people's best interests; competence or perception that technology has all functionality to provide effective help; and reciprocity or responding in kind by deciding to continually use technology if it has been helpful. Following the HCTS developers' guidelines for adapting it to specific contexts [22], we used the HCTS to assess students' trust in generative technology to support lifelong learning (shown in Appendix A). Students were asked to respond to each item using a five-point scale (1-strongly disagree; 5-strongly agree). The internal consistency value (Cronbach alpha) of the HCTS in this study was $\alpha = 0.90$.

2.3. Participants

To collect survey data, we used Prolific (Oxford, UK; www.prolific.com/researchers; accessed between April 2025 and June 2025), an online crowdsourcing platform that provides access to a vetted pool of participants for academic research [24]. Rather than relying on a single-institution sample prone to localized bias, we utilized Prolific as a sampling frame to secure a geographically diverse, multi-institutional sample of health professional students, strengthening both the external validity and generalizability of the study. To ensure sample validity, we leveraged Prolific's established background-verification procedures and participant verification infrastructure. As an internal layer of verification,

the survey included a question requiring respondents to specify their health professions education program as well as two attention-checking questions inserted at approximately equal intervals in the survey questionnaire.

On Prolific the survey was open to current students aged 25 or younger (born in 2000 or later) at the time of data collection. By limiting the sample to those aged 25 or younger, we aimed to capture individuals who have exclusively navigated contemporary learning environments. In total, 558 students (69% female) responded to the survey, with 267 (48%) residing in the Global South and 291 (52%) in the Global North. The respondents were students in health professions, including medicine ($n = 246$; 44%), nursing ($n = 125$; 22%), dentistry ($n = 29$; 5%), pharmacy ($n = 15$; 3%), and allied health professions ($n = 143$; 26%).

2.4. Data Analysis

Using IBM SPSS v. 29, we computed descriptive statistics (frequencies, means, standard deviations). Because our objective was to explore, rather than confirm or test, the underlying structure of the SPArKED items, we conducted an exploratory factor analysis (EFA), using principal component extraction with varimax rotation. We chose this approach because our goal was to examine how the items naturally grouped together rather than to isolate latent factors. We used the Kaiser–Meyer–Olkin (KMO) test and Bartlett’s test of sphericity to ensure the data and sample size were sufficient. KMO values between 0.8 and 1 and a significant Bartlett’s test indicate sample adequacy. To determine component retention, we evaluated the scree plot for the point of inflection alongside the eigenvalue-greater-than-one threshold. A 0.30 component loading threshold was applied. We used Cronbach alpha (α) as a measure of internal consistency and Pearson’s correlation coefficients to examine associations for the study variables.

3. Results

Means (SD) and percent agreement for the SPArKED items are shown in Table 1. Students reported exploring new topics primarily through digital resources (item 1; 97% agreed) and taking advantage of free digital resources (item 3; 94% agreed). Further, students reported using digital technology largely for individual learning, such as using online tutorials or how-to videos to enhance their skills (item 6; 90% agreed) and using online assessment tools to gauge their understanding of topics (item 8; 84% agreed). This is compared to collaborative learning where the percent agreement was lower, such as participating in online study groups or peer collaboration platforms (item 10; 47% agreed) and contributing to online forums or communities by sharing their knowledge and experiences (item 13; 48% agreed).

The EFA was performed with the SPArKED data next. The KMO index of sampling adequacy of the data in the current sample was 0.87, and Bartlett’s test of sphericity was statistically significant ($\chi^2(120) = 3347.73$, $p < 0.001$), thus meeting the requirements for factor analysis. The EFA showed that a 3-component structure best represented the data, yielding three components with eigenvalues greater than one and explaining 55% of the total variance in the SPArKED items. The three-component solution was also supported by the scree plot.

All the items exhibited strong primary loadings on specific components, with all primary loadings exceeding 0.30 (shown in Table 2). Although items 2, 5, and 7 cross-loaded, their primary loadings were higher on Component 2. A content review of these items confirmed that their underlying constructs aligned more closely with Component 2 than Component 1.

Table 2. EFA results of the SPARKED items (n = 558 students), rotated coefficients (loadings ≤ 0.30 are suppressed).

Item by Number		Component 1	Component 2	Component 3
12	I engage in live Q&A sessions or webinars hosted by experts in my field.	0.83		
10	I routinely participate in online study groups or peer collaboration platforms.	0.81		
13	I actively contribute to online forums or communities by sharing my knowledge and experiences.	0.81		
14	I participate in virtual seminars or conferences related to my professional interests.	0.80		
11	I seek learning opportunities through social media or professional networks.	0.67		
15	I follow social media for new ideas and trends in my field/profession.	0.34		
3	I take advantage of free digital resources to enhance my knowledge and skills.		0.70	
1	I explore new topics primarily through digital resources.		0.65	
6	I use online tutorials or how-to videos to learn or enhance my skills.		0.62	
8	I use online assessment tools like quizzes to gauge my understanding of topics.		0.59	
7	I take advantage of online simulations or interactive tools to practice new skills.	0.39	0.56	
5	I leverage digital tools like apps, podcasts, and e-books in my self-paced learning.	0.38	0.51	
2	I engage in online learning even when there are no deadlines or external accountability.	0.41	0.50	
4	I always assess the credibility of digital resources I use for self-study.		0.47	
9	I use AI-powered tools like ChatGPT and virtual tutors to assist me in my learning.			0.92
16	I use generative AI tools like ChatGPT to explore and develop my ideas.			0.91
Eigenvalue (% variance explained)		3.9 (24.4%)	3.0 (18.5%)	1.9 (11.7%)
Mean (SD)		2.68 (0.70)	3.26 (0.44)	3.07 (0.84)

When looking at the items that are loaded on each component, six items had the largest coefficients on Component 1, explaining 24.4% of the total variance (shown in Table 2). Based on the magnitude of the eigenvalue and the content of these items, Component 1 ($\alpha = 0.86$) was reflective of *networked learning* or digital learning that arises from social and professional relations or networks.

Eight items had the largest coefficients on Component 2, explaining 18.5% of the total variance (shown in Table 2). Based on the content of these items, Component 2 ($\alpha = 0.78$) was reflective of *i-learning* or digital learning for individual mastery.

Two items had the largest coefficients on Component 3, explaining 11.7% of the total variance (shown in Table 2). Based on the content of these items, Component 3

($\alpha = 0.87$) was reflective of *AI-powered learning* or learning with AI for facilitated insight and guided understanding.

Next, the SPArKED correlated positively and moderately with the JeffSLL-HPS ($r = 0.75, p < 0.001$), demonstrating convergent validity. The correlations between the SPArKED and the basic psychological needs were as follows: autonomy ($r = 0.50, p < 0.001$), competence ($r = 0.48, p < 0.001$), and relatedness ($r = 0.51, p < 0.001$), indicating positive associations between students' psychological need satisfaction and digital-age learning behaviours measured by the SPArKED items. Finally, the SPArKED correlated more strongly with the HCTS ($r = 0.52, p < 0.001$) than the JeffSLL-HPS did ($r = 0.32, p < 0.001$), suggesting that the SPArKED better explains students' trust in generative technology to support lifelong learning.

4. Discussion

Lifelong learning constitutes a critical component of professional competence and quality care in the health professions. While well-established, this concept continues to evolve. As digital technologies transform both professional practice and education, there is a growing need to evaluate digital-age learning behaviours and their influence on competence development and maintenance (lifelong learning). To facilitate such investigations, we developed the SPArKED (Self-Pursuits, Aspirations, and Knowledge Endeavors in the Digital Era) instrument and gathered content and convergent validity evidence.

First, using exploratory factor analysis, we observed three components underlying the SPArKED items: i-learning, networked learning, and AI-powered learning. Mean scores were highest for i-learning and AI-powered learning and lowest for networked learning. This prioritization of individual and AI-assisted learning echoes personalized learning trends identified in a systematic review on the impact of generative AI in health professions education [25]. Taken together, these trends have implications for professional identity formation, which inherently relies on community socialization and peer interaction [26]. By prioritizing individual mastery and AI-driven learning, students risk experiencing a form of professional isolation, impeding the internalization of professional values that can only be cultivated through social interaction across learning environments [26].

Second, positive associations between students' basic psychological needs and SPArKED scores suggest that the digital-age behaviours measured by the SPArKED appear to support students' needs for autonomy, competence, and relatedness. A recent study examining residents' use of digital resources for self-directed learning [2] similarly highlighted the role of basic psychological needs in residents' learning behaviours. Specifically, residents' needs for competence and relatedness to peers, upcoming role and patients promoted the continued use of digital resources within clinical settings. Outside of clinical care, residents prioritized autonomy, opting for digital resources that seamlessly fit their lifestyle [2].

Third, there was a moderate correlation between the SPArKED and the Jefferson scale (JeffSLL-HPS), a widely used, although dated, measure of lifelong learning in the health professions. It is important to note, however, that the JeffSLL-HPS also includes items measuring professional learning beliefs and motivation (the *why*), whereas the SPArKED aims to measure self-initiated learning and information seeking (the *how*) within contemporary digital realities. Depending on specific objectives, researchers can choose what measure better suits their investigative goals and contexts, thereby contributing further validity evidence.

Finally, the finding that the SPArKED better explains students' trust in generative technology to support lifelong learning highlights the evolving learning paradigms among younger generations. In educational contexts that increasingly lack viable human options

or alternatives, digital and recently generative technology becomes the always-available, trusted companion for students on their journey of acquiring profession-specific knowledge and skills [27]. Students are often fascinated with and rely on the technical performance of such technology [8,27], thereby explaining the observed trust students place in this technology to support their lifelong learning.

This study has several limitations. Because of the cross-sectional study design, causal inferences cannot be drawn; future research should include longitudinal studies. The research sample consisted of students in health professions, with more female participants (69%) represented. As such, the generalizability of the findings to non-health professions, other educational levels (e.g., residents), or sociodemographic contexts may be limited. Although the sample included health professional students residing in the Global South and the Global North countries, differences in health education systems may pose cultural or educational bias. While Prolific mitigated localized institutional bias, it carries inherent risks of self-selection bias. To minimize these effects, the study invitation was framed neutrally to ensure a broad appeal beyond tech-enthusiastic students. Additionally, given the use of survey-based measures, self-report bias may have influenced participants' responses. Finally, the AI-powered learning component of SPArKED consisted of two items. While the observed internal consistency for this component was high, the component may not fully capture the complexity of students' engagement with AI.

5. Conclusions

The study highlights the pressing need to align lifelong learning measurement with contemporary digital realities, necessitating a re-assessment of established instruments in health professions. To this end, we developed and evaluated the SPArKED instrument for measuring digital-age learning behaviours. Further research is essential to examine how SPArKED performs in different samples of health trainees, including across educational stages (pre-clinical versus clinical) and academic levels (low-performing versus high-performing trainees), as well as in other professions. This nuanced understanding can guide professional education programs in cultivating digital literacies and professional competencies among future practitioners, ultimately preparing them for lifelong learning.

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Institutional Review Board Statement: The study was conducted in accordance with the Declaration of Helsinki, and approved by the Research Ethics Board of the University of Alberta (REB #Pro00102091; date of approval: 17 April 2025) prior to data collection.

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study. In accordance with the study information letter provided to prospective participants, the act of submitting the completed survey served as formal participant consent.

Data Availability Statement: The data presented in this study are available on request from the corresponding author, provided the data request is within the study ethical approval.

Conflicts of Interest: The authors declare no conflicts of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

Appendix A

Table A1. The Jefferson Scale of Lifelong Learning—Health Professions Students Version (JeffSSL-HPS).

Items	Strongly Disagree	Disagree	Agree	Strongly Agree
1. Searching for the answer to a question is, in and by itself, rewarding.	1	2	3	4
2. Lifelong learning is a professional responsibility of all healthcare providers.	1	2	3	4
3. I enjoy reading articles in which issues of healthcare/medicine are discussed.	1	2	3	4
4. I routinely attend student study groups.	1	2	3	4
5. I read healthcare/medical literature in journals, websites or textbooks at least once every week.	1	2	3	4
6. I routinely search electronic resources to find out about new developments in healthcare/medicine.	1	2	3	4
7. I believe that I would fall behind if I stopped learning about new developments in healthcare/medicine.	1	2	3	4
8. One of the important goals of health professions' education is to develop students' lifelong learning skills.	1	2	3	4
9. Rapid changes in health science/medicine require constant updating of knowledge and development of new professional skills.	1	2	3	4
10. I always make time for learning on my own, even when I have a busy class schedule and other obligations.	1	2	3	4
11. I recognize my need to constantly acquire new professional knowledge.	1	2	3	4
12. I routinely attend optional sessions, such as professional meetings, guest lectures, or clinics where I can volunteer to improve my knowledge and clinical skills.	1	2	3	4
13. I take every opportunity to gain new knowledge/skills that are important to my discipline.	1	2	3	4
14. My preferred approach in finding an answer to a question is to consult a credible resource such as a textbook or electronic resource.	1	2	3	4

Table A2. Basic Psychological Needs Scale (adapted from the Psychological Need States in Sport Scale).

As I Continue to Learn, I . . .	Strongly Disagree			Neither Disagree Nor Agree			Strongly Agree	
1. Feel free to make choices with regards to the way I learn	1	2	3	4	5	6	7	

Table A2. *Cont.*

As I Continue to Learn, I . .	Strongly Disagree			Neither Disagree Nor Agree			Strongly Agree
2. Feel that I am capable	1	2	3	4	5	6	7
3. Feel supported	1	2	3	4	5	6	7
4. Have a say in how things are done	1	2	3	4	5	6	7
5. Feel skilled	1	2	3	4	5	6	7
6. Feel cared for	1	2	3	4	5	6	7
7. Have the freedom to make learning decisions	1	2	3	4	5	6	7
8. Am able to overcome challenges	1	2	3	4	5	6	7
9. Feel connected	1	2	3	4	5	6	7
10. Pursue goals that are my own	1	2	3	4	5	6	7
11. Feel confident that I can do well	1	2	3	4	5	6	7
12. Feel accepted	1	2	3	4	5	6	7
13. Feel like I can be myself	1	2	3	4	5	6	7
14. Feel that I am good	1	2	3	4	5	6	7
15. Like the people I interact with	1	2	3	4	5	6	7

Autonomy satisfaction: items 1, 4, 7, 10, 13; Competence satisfaction: items 2, 5, 8, 11, 14; Relatedness satisfaction: items 3, 6, 9, 12, 15.

Table A3. Human Computer Trust Model (HCTM) Scale (adapted to reflect trust in generative technology to support lifelong learning).

Items	Strongly Disagree		Neither Disagree nor Agree		Strongly Agree
1. I believe that there could be negative consequences when using generative AI like ChatGPT as part of my lifelong learning. *	1	2	3	4	5
2. I feel I must be cautious when using generative AI to support my lifelong learning. *	1	2	3	4	5
3. It is risky to interact with generative AI as a source of lifelong learning. *	1	2	3	4	5
4. I believe that generative AI will act in my best interest for lifelong learning.	1	2	3	4	5
5. I believe that generative AI will do its best to help me if I need help continuing my learning.	1	2	3	4	5
6. I believe that generative AI is interested in understanding my needs and preferences for lifelong learning.	1	2	3	4	5
7. I think that generative AI is competent and effective in supporting my lifelong learning.	1	2	3	4	5
8. I think that generative AI performs its role as a learning assistant/tutor for lifelong learning very well.	1	2	3	4	5
9. I believe that generative AI has all the functionalities I would expect from a learning assistant/tutor supporting lifelong learning.	1	2	3	4	5

Table A3. Cont.

Items	Strongly Disagree		Neither Disagree nor Agree		Strongly Agree
10. If I use generative AI, I think I would be able to depend on it completely for lifelong learning.	1	2	3	4	5
11. I can always rely on generative AI for objective feedback in my learning.	1	2	3	4	5
12. I can trust the information presented to me by generative AI to support my learning.	1	2	3	4	5

* Items 1, 2, and 3 are reverse coded.

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