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Development and Validation of the Scale for Attitudes Towards Generative AI (SAGAI)

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ABSTRACT

The Scale for Attitudes towards Generative Artificial Intelligence (SAGAI) was developed to understand learners' attitudes and perceptions towards the use of generative AI technologies in educational settings. Grounded in theoretical frameworks such as technology acceptance, planned behaviour, diffusion of innovations and social identity, the scale focuses on capturing attitudinal dimensions—including perceived usefulness, expectancy, competency and anxiety—rather than directly measuring behavioural engagement. The instrument was created through a systematic process beginning with an extensive item pool informed by literature and theory, followed by expert review and pilot testing. Its validity and reliability were examined through exploratory factor analysis with 244 undergraduate students and subsequently cross-validated via confirmatory factor analysis with another sample of 243 students. The analyses resulted in a 23-item scale comprising four distinct factors, each reflecting a different aspect of learners' attitudes towards interacting with generative AI. Findings indicated that students generally held positive perceptions about GenAI's benefits and future potential, although some degree of apprehension persisted, particularly reflected in higher anxiety scores. Overall, SAGAI offers a reliable and valid tool for gaining insights into learners' attitudes, competencies and concerns regarding GenAI's role and integration in education, and its application across diverse contexts may support stakeholders in understanding the broader impact and transformative potential of these emerging technologies.

1 | Introduction

In recent years, the educational sector has undergone transformations in line with rapid advances in technology and personalised learning needs (Alenezi et al. 2023; Marienko et al. 2020; Megahed et al. 2022). These transformations are not merely an evolution but a fundamental shift in the way people conceive, deliver and engage with education. At the forefront of this shift stands generative artificial intelligence (GenAI), a class of machine learning models and algorithms endowed with the capacity to generate content (Akgun and Greenhow 2022). This content encompasses not only text but also images, multimedia, and a spectrum of digital artefacts that closely mimic human-like creativity and understanding (Elkhatat et al. 2023). The integration of GenAI into education has introduced new possibilities for redesigning pedagogical practices. It has the potential to transcend traditional educational boundaries and reshape teaching and learning processes (Chan and Hu 2023), addressing long-standing challenges (Pal et al. 2023) and opening up new avenues for innovation in education (Sjödin et al. 2023).

Given GenAI's potential to transform educational experiences, understanding how students perceive and feel about using these technologies is crucial, as such attitudes are known to be important predictors of actual engagement. Recent AI-education research highlights significant changes in instructional delivery and learning interaction patterns. Among the various AI paradigms, GenAI has shown remarkable promise in contributing to education. One of the foremost contributions is its capacity to enable personalised learning experiences (Akgun and Greenhow 2022; Huang et al. 2023; Karakose and Tülübaş 2023; Yu and Guo 2023). Through the analysis of individual learner profiles and preferences, GenAI systems can tailor instructional materials and learning pathways to the needs and abilities of each student (Murad et al. 2023). This level of personalisation has been shown to significantly enhance engagement and retention, thereby improving educational outcomes. Another contribution relates to the efficient creation of instructional content. It facilitates the creation of diverse learning materials, ranging from textual documents to multimedia and interactive simulations (Karakose and Tülübaş 2023). By automating content creation, GenAI not only saves valuable time but also allows for the provision of a rich array of learning resources that cater to different learning styles and preferences (e.g., Farrelly 2023; Michel-Villarreal et al. 2023; Yu and Guo 2023). The immediate and personalised feedback provided by GenAI technologies helps learners develop their ability to self-directed learning and reflection (Chiu et al. 2023). By providing tools and platforms for exploring complex problems, generating new hypotheses and discovering novel solutions, GenAI serves as a catalyst for educational research and development (Bozkurt et al. 2023; Fatmasari et al. 2023; Fergus et al. 2023; Rane 2023; Zhai 2023). Furthermore, it promotes a culture of innovation among students and educators, preparing them for the challenges and opportunities of the 21st-century knowledge economy. By understanding learner perceptions and concerns, policy makers can build on the insights gained to create instructional guidelines and new strategies for effective use of GenAI tools in teaching and learning in higher education (Chan and Hu 2023). Finally, recent empirical studies and real-world applications underscore the efficacy of GenAI in enhancing the educational experience (Chan and Hu 2023; Dickey et al. 2023; Pellas 2023; Wang and Wang 2023).

As educational institutions increasingly integrate GenAI, the need to measure and understand student attitudes towards these emerging tools becomes essential. Engagement has the potential to serve both as an indicator of how effectively students interact with GenAI and as a predictor of the technology's impact on learning outcomes. Various educational institutions and tech companies have begun integrating GenAI tools into their teaching–learning processes, illustrating the growing recognition of GenAI's value in education. Its integration into educational practices is an important development towards achieving better learning outcomes (Avgerinou et al. 2023; Çelik et al. 2023; Perera and Lankathilake 2023) and nurturing a culture of continuous learning and innovation. As GenAI's potential in education becomes increasingly evident, the need to comprehensively understand, assess and quantify perceptions becomes paramount within educational settings.

1.1 | The Need for a Scale Assessing User Perceptions of GenAI in Education

The landscape of AI in education has traditionally been dominated by back-end systems and robotic functionalities, which primarily focused on automation and efficiency without direct interaction with users. However, with the advent of GenAI, the focus has shifted significantly towards more interactive, user-facing applications, such as chatbots that assist, tutor and engage with learners in a conversational manner. These GenAI systems are designed to understand and process educational content, providing tailored assistance that adapts to individual learning needs, styles and progress.

However, the rapid integration of GenAI into learning environments has outpaced the availability of theoretically grounded measurement tools that can capture students' attitudinal dispositions towards these new forms of interaction. While several AI-related scales exist, most of them were developed for earlier generations of AI technologies and do not address learners' perceptions of conversational, co-creative, and pedagogically embedded GenAI systems. This mismatch has created a clear research problem: educators and researchers lack an instrument capable of assessing how students make sense of, emotionally respond to and judge the educational value of GenAI within real learning contexts.

Existing instruments were primarily designed to measure acceptance of automated or task-specific AI systems, which do not involve sustained dialogue, adaptive feedback, or content generation. GenAI fundamentally alters the learner–technology relationship, shifting from tool use towards interactive engagement. Because of this shift, new constructs—such as perceptions of human-like interaction, co-creation and pedagogical alignment—have become central to understanding attitudes. These constructs are not captured in previous AI scales, making it necessary to develop a measurement tool that reflects the affordances, risks and experiential qualities unique to GenAI.

Our newly developed Scale for Attitudes towards Generative AI (SAGAI) is designed to capture this fundamental shift in how learners interact with AI systems. Unlike previous scales, a synopsis of which is outlined in Table 1, which typically assess the impact of AI using metrics such as efficiency and non-interactive, task-specific automation, the SAGAI focuses on the integration, interaction and pedagogical impact of GenAI in educational settings. By focusing on attitudes towards engagement with an advanced technology characterised by human-like interaction, SAGAI aims to measure not only the extent of use but also the depth of interaction between learners and GenAI, thereby reflecting how these technologies are being incorporated into the learning process and their potential to enhance educational outcomes. In doing so, SAGAI captures attitudinal factors that shape the extent and quality of learners' interaction with GenAI, without directly measuring behavioural engagement.

All this would not be meaningful if we did not specifically direct the attention of participants to the new capabilities of GenAI. As described in the Method section, to ensure clarity and precision in how respondents understand and evaluate GenAI, we provided comprehensive guidelines that define GenAI in the context of education-centric tasks it can perform. This includes brief but clear descriptions of GenAI capabilities, ensuring that participants are well informed about the specific nature and potential of GenAI before they respond to the scale items.

Research has shown that learners' favourable attitudes can enhance their academic performance (Cukurova et al. 2020).

TABLE 1 | Summary of existing AI attitude and acceptance scales in education and their limitations.

Scale	Target audience	Main constructs	Technology focus	Gaps addressed by SAGAI
Suh and Ahn (2022)	K–12 students	General attitudes (interest, usefulness, threat)	AI (general)	Not tailored to higher education or GenAI; lacks expectancy and competency constructs.
Schepman and Rodway (2020)	Adults	Positive/negative attitudes, trust	AI (general)	No focus on education or GenAI-specific interactive capabilities.
Ustun et al. (2023)	Undergraduate students	UTAUT-based acceptance	Virtual reality	Not AI-focused; omits anxiety and future expectancy dimensions.
Sezer and Yilmaz (2019)	Undergraduate students	LMS acceptance	LMS platforms	No AI context; lacks competency, anxiety and GenAI focus.
Terzi (2020)	Teachers	AI anxiety	AI (general)	Single-dimension focus; no positive attitudes or expectancy.
Grassini (2023)	Adults	Utility, societal impact	AI (general)	Short scale; not education-specific; no competency or expectancy.
Yilmaz et al. (2023)	Undergraduate students	GenAI acceptance	GenAI	Focuses only on acceptance; lacks anxiety as a barrier and theoretical integration.
Sindermann et al. (2021)	Adults	Cross-cultural attitudes	AI (general)	No education context; lacks dimensions relevant to learning settings.
Park et al. (2024)	Adults	Workplace AI attitudes	AI (general, workplace)	Limited to work settings; not applicable to higher education.

Note: As seen above, no existing instrument combines the following: (1) multiple theoretical foundations (TPB, TAM, SIT, DIT), (2) balanced coverage of positive (usefulness, expectancy, competency) and negative (anxiety) attitudes and (3) a specific focus on GenAI's interactive, creative and adaptive functions in higher education. SAGAI was designed to address all three of these gaps.

Analysis of such attitudes can assist educators in optimising instructional materials (Yu et al. 2012). According to Schepman and Rodway (2020), people's overall attitudes towards AI are likely to significantly influence their acceptance of AI. Hence, to effectively implement GenAI in education, it is imperative to assess and comprehend students' perspectives and dispositions towards GenAI.

SAGAI is designed to capture learners' attitudes towards engagement with GenAI in order to facilitate its integration by providing insights into its effectiveness as an educational tool, suggesting ways for educators to refine teaching strategies based on GenAI's capabilities, offering a framework to gauge its influence on educational outcomes, addressing potential ethical considerations and assisting in the exploration of its long-term impact on education through ongoing study. By measuring attitudes, SAGAI provides insights into the interactive and pedagogical aspects of GenAI, guiding educators in refining teaching strategies and maximising the potential of GenAI to enhance learning outcomes.

2 | Theoretical Background

GenAI refers to advanced AI systems capable of creating new and original content such as text, images, audio, video, and code, based on patterns learned from large datasets. Unlike traditional AI, which is primarily used for classification or prediction, GenAI produces novel outputs that can mimic human creativity and problem-solving. Popular examples include text-based tools such as ChatGPT, Gemini and Claude, image generation tools such as DALL·E and Midjourney, and code generation systems like GitHub Copilot. In educational contexts, GenAI can facilitate the creation of personalised learning materials, generate practice exercises, simulate interactive scenarios and support research activities, thereby offering transformative potential for teaching and learning.

2.1 | Attitude

Attitude, foundational to the discipline of social psychology, encapsulates an individual's evaluative judgements concerning specific entities, whether favourable or unfavourable (Schwarz and Bohner 2001; Albarracin et al. 2005). These evaluative judgements, often seen as the sum of feelings, beliefs, and behaviours towards an entity, play pivotal roles in guiding actions, shaping perceptions and influencing interpersonal dynamics (Ajzen and Fishbein 2005). More recent studies have underscored that attitudes are not merely static assessments but are malleable, influenced by both internal cognitive processes and external social factors (Albarracín et al. 2018). Additionally, the formation and change of attitudes are intricately linked with one's social identity, cultural background and personal experiences, making them complex constructs shaped by both personal and contextual factors (Hamamura 2017).

Attitude is defined as consisting of three complementary components (Metsärinne and Kallio 2016). *Emotional/affective dimension* pertains to the emotional reactions an individual associates with a specific object or topic, encompassing feelings that can range from love to hate, happiness to sadness (Clore and Palmer 2009). *Cognitive dimension* encompasses the beliefs, perceptions, and knowledge one holds about the entity in question, providing a structured framework to interpret and rationalise experiences (Petty et al. 2007). Reflecting the tangible manifestations of internal sentiments, *behavioural dimension* elucidates how individuals are predisposed to act or behave concerning the focal entity (Perugini and Bagozzi 2001).

The relationship between attitude and engagement is particularly important when considering the adoption and use of new technologies like GenAI in educational settings. A positive attitude towards GenAI can significantly enhance a student's engagement with the technology, leading to deeper interaction and more meaningful learning experiences. Conversely, the level of engagement a student has with GenAI can also influence their attitude over time.

As our understanding of human behaviour and cognition evolves, attitudes remain at the forefront of research (Petty et al. 1997), with scholars continuously probing their formation, change and impact on human behaviour. Based on this understanding, the following theories provide complementary lenses in investigating attitude as a determinant of the use of new technologies or GenAI.

2.2 | Theoretical Constructs & Interrelationships Linked With Attitudes Towards GenAI

Attitudes play a central role in shaping intentions and behaviours, and several theoretical frameworks help explain their significance in the context of Generative AI (GenAI). Four key models—Theory of Planned Behaviour (TPB), Technology Acceptance Model (TAM), Social Identity Theory (SIT) and Diffusion of Innovation Theory (DIT)—provide distinct yet interrelated perspectives on the factors shaping attitudes towards GenAI in educational contexts.

The TPB (Ajzen 1985) suggests that individual behaviour is driven by behavioural intentions, which in turn are shaped by attitudes towards the behaviour, subjective norms and perceived behavioural control. In educational settings, students' attitudes towards learning and technology significantly influence their intentions to adopt new tools. In the context of GenAI, TPB explains how attitudes impact the intention to use or engage with these technologies.

The TAM (Davis 1989) posits that perceived usefulness and perceived ease of use determine an individual's intention to use a technology. In relation to GenAI, TAM helps explain how learners' perceptions of its utility and user-friendliness influence their attitudes. Variants such as TAM2 (Venkatesh and Davis 2000) and UTAUT (Venkatesh et al. 2003) expand on these constructs but retain the core premise.

SIT (Tajfel and Turner 1979) highlights the role of group membership in shaping identity, leading to in-group favouritism and out-group bias. In GenAI adoption, learners may identify with groups such as 'tech-savvy users' or 'traditionalists', influencing their openness or resistance to adoption.

DIT (Rogers 1995) examines how innovations spread through populations over time, emphasising attributes such as relative advantage, compatibility, complexity, trialability and observability. Applied to GenAI, DIT provides insights into how attitudes evolve during the diffusion process and how adoption patterns emerge within educational communities.

This integrated perspective highlights how the four theories complement one another in explaining attitudes towards GenAI. TAM expands on the 'attitude' component of TPB by specifying two core beliefs—perceived usefulness and perceived ease of use—that directly influence technology adoption (Lee and Kozar 2008). SIT adds the dimension of group identity, showing how affiliation with certain user groups (e.g., tech enthusiasts) can shape these beliefs and attitudes (Johnson and Zhang 2015). DIT contributes a temporal and social diffusion lens, explaining how such attitudes and adoption patterns evolve and spread across communities (Roberts and David 2017).

Taken together, these theories converge on the idea that GenAI-related attitudes emerge not from a single determinant but from the interaction of cognitive appraisals (TAM), motivational and control beliefs (TPB), social identity influences (SIT) and perceptions of innovation attributes (DIT). This interconnected structure reflects the multifaceted nature of GenAI, which operates simultaneously as a tool, a social actor and an evolving innovation within learning environments.

2.2.1 | Integrated Theoretical Framework

Building on these foundations, the development of the SAGAI scale was guided by four complementary theories: the Theory of Planned Behaviour (TPB), the Technology Acceptance Model (TAM), Social Influence Theory (SIT) and Diffusion of Innovations Theory (DIT). Rather than prescribing fixed factors a priori, these theories served as guiding lenses to identify potential domains of GenAI adoption that required systematic measurement. Their integration ensured that the instrument was grounded in established behavioural and educational technology models while remaining open to empirical validation through EFA and CFA.

Although each theory contains multiple constructs, only those directly relevant to GenAI-driven learning experiences were used to guide initial item generation. For example, TAM provides four primary constructs; however, perceived usefulness and ease of use were prioritised because GenAI adoption in learning settings is strongly driven by perceived utility rather than interface control. Similarly, TPB includes subjective norms and perceived behavioural control, but only attitude-relevant elements were incorporated because SAGAI focuses specifically on attitudinal dispositions rather than behavioural prediction. From SIT, identity alignment and perceived group belonging were emphasised, whereas intergroup comparison was excluded due to limited relevance in GenAI learning contexts. Finally, from DIT, only innovation-related perceptions that students can meaningfully judge—aspects such as relative advantage and perceived compatibility—were considered. This selective integration ensured theoretical grounding while preventing construct overload.

TPB highlights attitudes towards behaviour, perceived behavioural control and intention. This theoretical lens addresses the gap that existing scales often overlook motivational and control-related dimensions that shape adoption. TAM emphasises usefulness and perceived ease of use, directly addressing the gap that many AI literacy instruments fail to capture users' perceptions of practical utility. SIT accounts for the role of peers, instructors and broader social norms, responding to the gap that prior scales have rarely included external influences on AI adoption in higher education. DIT introduces innovation characteristics such as relative advantage, complexity and compatibility, which help explain variability in adoption decisions and address the gap that current instruments largely neglect contextual and innovation-specific factors.

Taken together, these theoretically informed decisions ensured that the initial item pool was grounded in well-established models while remaining responsive to the unique interactional and generative qualities of GenAI. The theories functioned as conceptual lenses rather than prescriptive factor structures, meaning that item–construct alignments were treated as starting hypotheses that were tested and refined through empirical analyses.

When these theories are considered together, the SAGAI framework moves beyond fragmented explanations towards a cohesive foundation. Together, the four theories illuminate motivational, functional, social and innovation-related dimensions that have been underexplored in previous measures. These theoretical insights informed the design of the initial item pool and provided a rationale for anticipating multi-dimensionality, which was subsequently tested and refined through empirical analyses.

3 | Literature Review

A variety of instruments have been developed to measure attitudes towards artificial intelligence (AI) and related technologies. These instruments vary in scope, constructs, target populations and technological focus. Table 1 summarises the main characteristics of these scales, their contexts and the specific gaps addressed by the SAGAI.

In parallel with the development of these measurement instruments, recent studies have explored how GenAI-related engagement is shaped by learning climates, affordances and motivational factors in higher education (e.g., studies on AI-assisted EFL classroom climate, affordance-driven learning behaviour and UTAUT extensions in AI-mediated language learning). Collectively, these studies show that GenAI adoption is influenced not only by cognitive perceptions but also by emotional responses, classroom environments and motivational drivers—factors that existing AI attitude scales do not fully capture. This reinforces the need for a dedicated, theoretically grounded measurement instrument.

3.1 | Detailed Overview of Existing Scales

Research on attitudes towards AI and related technologies has produced a diverse set of instruments, varying in context, population and focus. Some scales were developed for younger learners or teachers. For example, Suh and Ahn (2022) developed a 26-item instrument to measure K–12 students' attitudes towards AI, including interest, perceived usefulness and perceived threat. While comprehensive for younger learners, it is not tailored to higher education and does not address specific generative AI features or constructs such as future expectancy and user competency. Similarly, Terzi (2020) adapted an AI Anxiety Scale for teachers, capturing various anxiety dimensions. However, its narrow scope excludes positive attitudes, expectancy or perceived competency. Together, these examples show that instruments developed for K–12 or teacher populations do not capture the attitudinal dimensions relevant to university students interacting with GenAI.

Other instruments target the general population. Schepman and Rodway (2020) created the General Attitudes Towards Artificial Intelligence Scale (GAAIS) for adults in the United Kingdom, focusing on positive/negative attitudes and trust. Grassini's (2023) AI Attitude Scale (AIAS-4) similarly emphasises utility and societal impact in a concise format. Although both offer insight into public perceptions, they do not account for the interactive, content-generating capabilities of GenAI or the educational context.

A further group of studies examined technology adoption beyond AI. Ustun et al. (2023) measured virtual reality acceptance among undergraduates using a UTAUT-based model. Despite its relevance to technology adoption, its focus on VR rather than AI and omission of GenAI-specific constructs like anxiety or expectancy limit its applicability. Likewise, Sezer and Yilmaz (2019) developed the Learning Management System Acceptance Scale (LMSAS), which, although not AI-specific, demonstrates how TAM-based frameworks have been successfully adapted to educational technologies. This link is particularly relevant for the present study, as TAM underpins the construct of usefulness in GenAI adoption. However, LMSAS does not capture AI- or GenAI-related competencies, underlining the limitations of relying on proxies such as LMS or VR tools.

Some recent instruments explicitly address GenAI or AI in educational settings. Yilmaz et al. (2023) examined undergraduates' acceptance of GenAI through a 20-item scale. While specific to GenAI, it focuses primarily on acceptance and does not integrate multiple theoretical frameworks or address anxiety as a potential barrier. Sindermann et al. (2021) compared attitudes towards AI across Germany, England, and China using a 5-item measure, and Park et al. (2024) developed a workplace-oriented scale. Both studies contribute valuable contextual insights but are either too general or too workplace-specific to address higher education learners' engagement with GenAI.

Taken together, these instruments reveal three key limitations. First, many are context-specific (K–12, workplace, LMS, VR) and not tailored to higher education students. Second, they often focus on either positive or negative attitudes rather than integrating both. Third, they fail to capture constructs unique to generative AI, such as future expectancy, user competency, and anxiety as both a barrier and a lens for adoption. Addressing these gaps, the present study develops a theoretically grounded and psychometrically validated scale that specifically measures higher education students' attitudes and perceptions towards GenAI technologies, thereby contributing a novel instrument to the literature. Overall, the diversity of prior AI-related instruments—and their lack of focus on the interactive, generative, and pedagogically embedded nature of GenAI—reveals a clear conceptual gap that current measurement tools do not address. Addressing this gap requires a theoretically grounded scale specifically tailored to attitudinal responses in higher education contexts, where GenAI is rapidly becoming a central learning partner rather than a background technology. Accordingly, this study was guided by the following overarching research question (RQ): *How can a theoretically grounded and empirically validated scale be developed to measure learners' attitudes and perceptions towards Generative AI in higher education?*

4 | Method

This is a scale development and validation study. The development process followed established best practices for instrument construction (DeVellis 2017; Hinkin 1998), involving several stages beginning with the generation of items to be included in the scale, followed by expert review and refinement, and subsequent pilot testing. Exploratory factor analysis (EFA) was then applied to evaluate the factorial structure of the initial item pool, and confirmatory factor analysis (CFA) was conducted to test the structural integrity of the final scale items. The initial stage, as well as the participants and procedures involved in the study, is detailed below, while the subsequent validation stages are elaborated in the Section 5.

4.1 | Item Generation

Prior to devising the initial version of the scale, several scale items were incorporated from the existing literature through a systematic review of studies on AI, attitudes towards AI and technology adoption (see Section 3), including Suh and Ahn (2022), Schepman and Rodway (2020), Ustun et al. (2023), Sezer and Yilmaz (2019) and Terzi (2020). In addition to these, publications on AI and attitudes towards it in general (e.g., Aydın et al. 2022; Mousavi Baigi et al. 2023; O'Shaughnessy et al. 2023; Pedrycz et al. 2024) were examined while incorporating the items for inclusion in the item pool. This process followed recommended best practices for scale development (DeVellis 2017; Boateng et al. 2018). The major theories related to them were thus identified, as presented in the theoretical background section. Each theory (TAM, TPB, SIT, DIT) was examined at the construct level; however, only constructs directly relevant to attitudinal judgements towards GenAI were included. For example, TAM contains four constructs (perceived usefulness, perceived ease of use, attitude towards use, behavioural intention), but behavioural intention was excluded because SAGAI aims to measure attitudes rather than behavioural prediction. Similarly, TPB constructs such as subjective norm and perceived behavioural control were reviewed, yet only attitude-relevant elements were included due to their conceptual fit with an attitudinal scale. From SIT, identity alignment and group belonging were retained, whereas intergroup comparison and bias-related constructs were removed as they do not meaningfully apply to GenAI use in learning contexts. For DIT, perceptions such as relative advantage and compatibility were included, while complexity and trialability were excluded because they reflect innovation diffusion rather than attitudes. In line with these decisions, the initial item pool was generated by mapping items to the theoretically retained constructs, ensuring representation without construct inflation (Eristi et al. 2010; Tomiuk and Pinsonneault 2009; Ustun et al. 2023). This resulted in an initial compilation of 86 items, ensuring broad coverage of theoretical constructs.

The distribution of items across the four theoretical frameworks is visually summarised in Figure 1a, where each framework is colour-coded and overlaps are explicitly indicated. For example, an item associated solely with TAM is 'Using AI enables me to accomplish tasks more quickly', while an example representing TPB is 'I want to make something that makes human life more convenient through AI'. For DIT, an example is 'I will choose a job in the field of AI'. SIT items, shown in the overlapping regions of Figure 1a, intersect with at least one other theory. For instance, an item pertaining to both SIT and TAM is 'I can be a good friend with AI', while another item overlapping DIT and SIT is 'People like me will suffer if AI is used more and more'.

Following the exploratory and confirmatory factor analyses, the final clustering of items into the SAGAI's factors is presented in Figure 1b. This figure visually links each empirically derived factor back to its theoretical origins, demonstrating how certain constructs (e.g., usefulness, expectancy, competency, anxiety) emerged as cohesive factors while others (e.g., subjective norm, trialability) did not manifest as distinct attitudinal dimensions. Colour-coding and connecting lines are used to make theoretical overlaps and distinctions clearer, in line with reviewer suggestions for improved visual representation.

To ensure content validity, nine academic professionals, all holding PhD degrees and expertise in educational technology and online learning, were invited to scrutinise each item for its necessity, content relevance and clarity. In this phase, an evaluation form was developed, featuring space and rating scale next to each item for experts to pen down their assessments, ensuring a thorough and systematic evaluation of the content. A 4-point rating scale was used (1 = item is inappropriate, 2 = item requires major revision, 3 = item needs minor revision, 4 = item is appropriate). Each expert rated the items independently. For each item, the Content Validity Index (CVI) was calculated based on expert ratings, and items with a CVI below 0.80 or a mean rating below 3.50 were removed or substantially revised, following the recommendations of Lynn (1986) and Polit and Beck (2006). After this threshold-based evaluation, overlapping or highly similar items were excluded or consolidated, resulting in a refined set of 56 items from the original pool of 86. The items in this preliminary version were then randomised and formatted into a five-point Likert-type scale, with rating options of 5 = strongly agree,

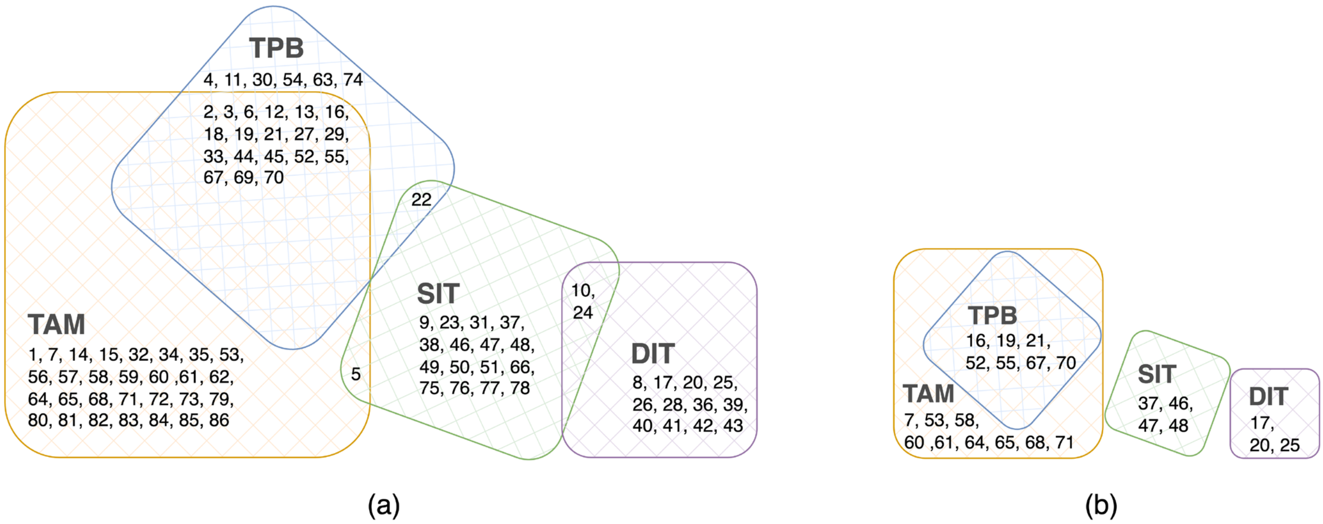

FIGURE 1 | (a) Initial item pool categorisation across four theoretical frameworks: TAM, DIT, SIT, TPB. (b) Final categorisation of scale items.

4 = agree, 3 = undecided, 2 = disagree and 1 = strongly disagree. Ensuring that participants could understand the scale items was a crucial step during item generation. To get opinions on this, a group of 13 graduate students were given the 56-item list and asked to share their interpretations of each statement. Their feedback was collected through individual cognitive interviews, and all comments were reviewed to identify language issues, redundancy or ambiguity. Based on their feedback, the items were rewritten to improve language, clarity, sentence structure and to reduce overall length. Items that were overly complicated or repetitive were eliminated, resulting in the retention of 47 items in the final pilot-ready version.

The final SAGAI instrument comprised 47 items distributed across four theoretically grounded dimensions (TAM, TPB, SIT, DIT), each rated on a five-point Likert scale (1 = strongly disagree, 5 = strongly agree). Higher scores indicate more positive attitudes towards generative AI in educational contexts. Example items for each dimension are shown in Figure 1a,b. Content validity was established through expert review, while face validity was ensured through graduate student feedback prior to data collection.

4.2 | Participants, Procedure & Data Analysis

In developing SAGAI, we used one sample set. The sample included 488 (215 males and 192 females) undergraduate students from two universities in Türkiye, accessed via the convenience sampling technique. Data were collected in the 2024–2025 academic year. Everyone who took part in the study did so voluntarily. They were told about the aim of the research as well as their right to withdraw from it at any point before, during, or after data collection. Informed consent was collected from all participants prior to data collection. The survey form included the scale as well as questions on demographic information. To ensure that all participants had at least a basic understanding of generative AI before responding, students were first provided with a short, structured tutorial including definitions, examples, and usage contexts of GenAI in education. They were then asked to try out GenAI tools such as ChatGPT and Gemini for 2 weeks through a detailed overview and provided links. This step was designed to minimise bias arising from unfamiliarity with GenAI technologies and to ensure responses reflected informed attitudes. After trying these tools, students were asked to complete the survey based on their understanding and what they experienced.

To test the psychometric qualities of the SAGAI scale, we chose to proceed with a two-stage approach where about one half of a randomly selected sample (EFA Sample) was utilised for exploratory factor analysis (EFA), and the remaining half (CFA Sample) for confirmatory factor analysis (CFA). Because the CFA does not accept missing values, we chose to eliminate the cases with missing values from both samples. This resulted in the EFA Sample to be $n = 227$ and the CFA Sample to be $n = 224$. Even though we chose and categorised the items based on the literature we reviewed, the assigned meanings of them ran the potential of overlapping across the SAGAI dimensions. As a result, the EFA Sample assisted us in both outlining the instrument's development and using EFA to examine the SAGAI's factor structure. CFA sample assisted us in confirming the observed factor structure by CFA and assessing the stability of the factors found in EFA Sample. EFA was performed using IBM SPSS Statistics version 26, and CFA was conducted using IBM SPSS AMOS version 21.

5 | Findings

5.1 | Exploratory Factor Analysis (EFA)

Prior to EFA, 47 items were examined for descriptive statistics to ensure their suitability for factorial analysis by using the EFA Sample. The means ranged from 3.09 to 4.30, and standard deviations ranged from 0.75 to 1.21. These values indicate an acceptable spread around the mean (Teo 2019). The skew indices (−1.52 to 0.05) and kurtosis indices (−0.97 to 3.09) were within the suggested ranges of |3.0| and |8.0| for skewness and kurtosis, respectively, indicating that the data had univariate normality (Kline 2016). We have reverse-coded the items that have negative meanings.

An EFA using principal components extraction and direct oblimin rotation was conducted on the 47 items (Bartlett's test of sphericity: $\chi^2(1081) = 3220.79$, $p < 0.001$; KMO = 0.91). In EFA, items may be removed from the analysis due to cross-loading, which occurs when an item loads significantly on more than one factor. The general guideline is to ensure that each item measures a construct and has higher loadings (preferably greater than |0.6|) in only one column or factor, while having smaller loadings with other constructs. According to Büyüköztürk (2007), if an item measures strongly (above |0.6|) on another construct, it is advisable to remove that item from the analysis. This is done to maintain the distinctiveness of each factor and to ensure that each construct is measured accurately. Through the principal components analysis, based on this logic, 25 items were removed and 23 items were kept for further analysis. This analysis resulted in four interpretable factors that accounted for 65.68% of the total variance explained. A large percentage of explained variance could be seen as a sign of the measurement quality of a pertinent construct (Büyüköztürk 2007).

Of the 23 items, Factor 1 (*usefulness*) comprises 10 items, Factor 2 (*anxiety*) comprises four items (all remaining reverse coded items grouped under this factor), Factor 3 (*expectancy*) comprises six items and Factor 4 (*competency*) comprises three items. The factor loadings ranged between 0.60–0.90 (usefulness), 0.67–0.90 (anxiety), 0.67–0.88 (expectancy) and 0.75–0.89 (competency). Importantly, each factor maps onto a specific theoretical dimension: usefulness (TAM), anxiety (TPB/DIT risk perceptions), expectancy (TPB behavioural beliefs) and competency (SIT—self-efficacy and identity alignment). This alignment confirms that the empirical structure corresponds closely with the conceptual foundation introduced earlier. A correlation matrix was obtained by using summed scores for each factor. All inter-factor correlations ranged from $r = |0.017|$ to $r = |0.611|$. This pattern—low to moderate correlations—indicates that although the factors are related, they retain conceptual distinctiveness, which supports the multidimensionality of the SAGAI.

The scale's reliability was examined using Cronbach's alpha reliability analysis. With respect to all 23 items of the scale, the Cronbach's alpha coefficient was 0.87. Reliability values were 0.93 (usefulness), 0.81 (anxiety), 0.89 (expectancy) and 0.80 (competency). All values exceeded the 0.70 threshold, demonstrating strong internal consistency (George and Mallery 2003). The SAGAI's principal components analysis (PCA) with varimax rotated solution is displayed in Table 2. Taken together, these results indicate that the EFA yielded a theoretically coherent and statistically robust four-factor structure, providing a strong foundation for proceeding to CFA.

The results of this stage show that the scores of the four-factor model are sufficiently reliable to move on to the SAGAI's next development stage.

5.2 | Confirmatory Factor Analysis (CFA)

To validate the factor structure derived from EFA, the data from the CFA Sample were used. To evaluate the adequacy of the measurement model, we performed a series of CFAs. With the CFA Sample, the four-factor, 23-item structure identified in the EFA was cross-validated through maximum likelihood estimation. Resulting fit indices for three different CFA models are presented in Table 3. The final model is shown in Figure 2.

The initial model (Model 1, the null model) demonstrated acceptable but improvable fit indices despite moderate-to-high item loadings on their intended factors. However, it did not meet the criterion for chi-square ($\chi^2/\text{df} < 2.0$) (Table 3). A model should be adjusted based on modification indices and theoretical justifications when an original model does not fit (Byrne 1998). Additionally, once the model fits properly and other models do not further improve the fit, researchers should stop fitting the model. The modification indices suggested additional covariance paths that would most significantly enhance the model fit between the error terms of e02 and e06 and items e18 and e19 (see Figure 2). After applying the indicated paths by rerunning the analysis, the model (Model 2) showed better fit across all indices compared to Model 1, indicating a more favourable match between the model and the data. Still, the chi-square failed to satisfy the requirements for an acceptable model fit ($p < 0.01$). The analysis suggested another covariance path between e03 and e10. These items were theoretically linked due to similarity in meaning and shared construct representation. After adding a covariance path between the error terms in question, the model was rerun. Model 3, the final model (Figure 2), demonstrated the best fit with all indices falling within excellent ranges, suggesting it is the most suitable model among the three for representing the underlying data structure (Table 3). None of the items had low loadings on their respective factors. In the final model, NFI value is within the acceptable limit values (Arbuckle 2003; Schumacker and Lomax 2004), and the other indices demonstrate a perfect fit (Tabachnick and Fidell 2007; Schumacker and Lomax 2004; Kline 2016). Collectively, these results confirm that the four-factor structure identified through EFA remains stable and theoretically coherent when tested via CFA.

According to the standard criteria in the literature (Flynn et al. 1990; Fornell and Larcker 1981; Hair et al. 1998), the acceptable thresholds for Cronbach's alpha, composite reliability and average variance extracted (AVE) are 0.7, 0.7 and 0.5, respectively. Good convergent validity is demonstrated by all these values for all constructs being more than 0.5, as shown in Appendix S1. To evaluate discriminant validity, we compared the square root of AVE of each construct with the correlation among the constructs; this is another method for assessing validity, discriminant validity (Fornell and Larcker 1981). Good discriminant validity is indicated if the square root of AVE is greater than the correlation between the components. For SAGAI, AVE square root values were all greater than the correlation values, as seen in Table 4. These findings together demonstrate that the SAGAI exhibits strong convergent and discriminant validity, further supporting the adequacy of the four-factor structure identified through EFA.

6 | Discussion and Conclusion

The main purpose of this research is to develop an instrument that can measure learners' attitudes towards engagement with GenAI technologies and their perceptions of the use of these technologies in educational settings. SAGAI has emerged as a

TABLE 2 | Results of the PCA with direct oblimin rotation.

Item	Variable	Statement[a]	F1	F2	F3	F4
1	USE01	GenAI allows me to do my work without getting tired	0.903			
2	USE02	GenAI enables me to do my work in less time	0.886			
3	USE03	GenAI allows me to do my work with less effort	0.826			
4	USE04	Using GenAI allows me to do my work faster	0.824			
5	USE05	Using GenAI makes my life easier	0.782			
6	USE06	I can prepare my work (homework, projects, etc.) using GenAI	0.781			
7	USE07	GenAI helps me do my work with fewer mistakes	0.687			
8	USE08	GenAI helps me to do my work with less stressful	0.687			
9	USE09	I can easily access the information I want from GenAI	0.613			
10	USE10	GenAI enables work to be done using fewer personnel	0.597			
11	ANX01	I think that GenAI can be dangerous		0.900		
12	ANX02	I shudder when I think about the advancement of GenAI		0.879		
13	ANX03	I am concerned that GenAI may eliminate some professions		0.690		
14	ANX04	The unethical use of GenAI technologies is worrisome		0.672		
15	EXP01	I think trainings on GenAI will be useful for me			−0.875	
16	EXP02	I think that GenAI should be included in education programmes			−0.820	
17	EXP03	I think trainings on GenAI are valuable for the future			−0.814	
18	EXP04	GenAI will play an active role in almost every field in the future			−0.762	
19	EXP05	I think that GenAIs will be present in every aspect of life			−0.728	
20	EXP06	I think that most future professions will require knowledge of GenAI			−0.666	
21	COM01	I am good at using GenAI				−0.890
22	COM02	I understand the language of GenAI				−0.758
23	COM03	I know how to get better results from GenAI				−0.752
Total Eigen Value			9.40	2.48	1.67	1.56
Total Variance Explained			40.86	10.80	7.25	6.77

Note: F1: usefulness; F2: anxiety; F3: expectancy; F4: competency.
[a]These are the English translations of the items that were originally administered in Turkish. The original items in Turkish are presented in Appendix S2.

23-item instrument with a five-point Likert scale that assesses learners' perceptions of GenAI in four dimensions. While several instruments exist for AI more broadly, they were designed for earlier forms of automated or task-specific AI and therefore do not capture attitudes towards interactive, dialogic and generative systems. The findings of this study address this gap by providing a theoretically grounded measure aligned with the experiential features of GenAI. SAGAI's CFA results affirmed the four-factor model as the most suitable compared to alternative models—as expanded upon below—with all items showing strong factor loadings. The factors were significantly correlated but distinct, suggesting nuanced dimensions within the scale

TABLE 3 | The model fits of CFA model of the SAGAI.

	χ^2	χ^2/df	TLI	CFI	NFI	IFI	RMSEA	SRMR
Model 1 (null model)	454.573	2.03	0.92	0.93	0.86	0.93	0.07	0.063
Model 2	412.654	1.85	0.94	0.94	0.89	0.94	0.06	0.063
Model 3 (final model)	399.119	1.81	0.95	0.95	0.90	0.95	0.06	0.063

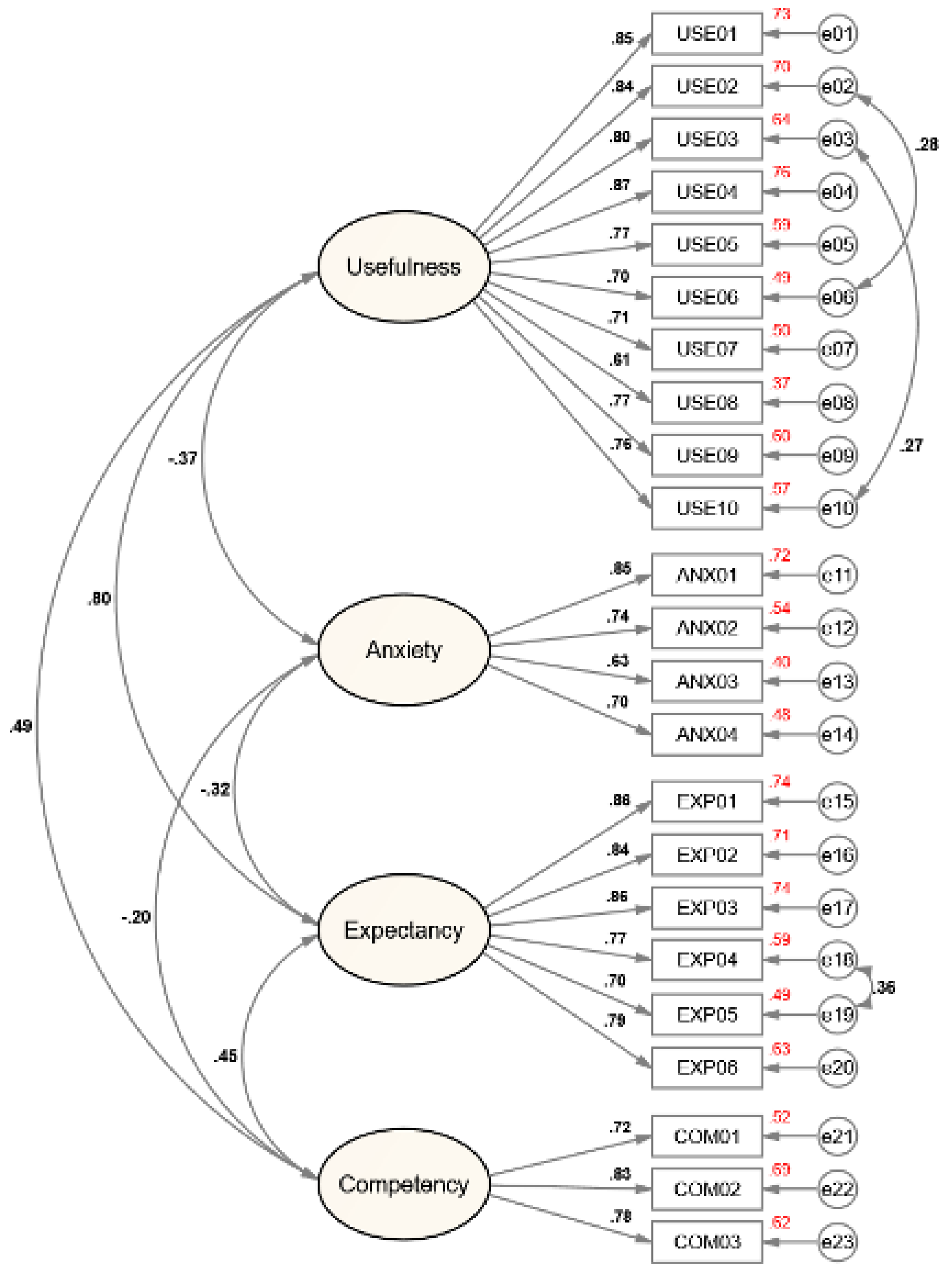

FIGURE 2 | CFA results (Model 3, standardised estimates). Red values show R^2 values.

and supporting a multidimensional interpretation of GenAI attitudes without overstating predictive or causal implications.

This paragraph outlines how the factors in the scale should be interpreted for meaningful use of the results. On a factor basis, scores can range from a minimum of 1.00 to a maximum of 5.00. A high mean score on *usefulness* indicates that users view GenAI as an effective and useful tool. *Anxiety* reflects the extent to which users experience worry or apprehension when using GenAI; in SAGAI, lower anxiety contributes to a higher overall scale score because the items in this factor are reverse-coded. A high score on *expectancy* denotes strong positive expectations about the future role and widespread adoption of GenAI. *Competency* captures how capable participants feel in using

TABLE 4 | Descriptive statistics, correlation matrix, reliability and square root of AVE.

Order	Factor	M	SD	F1	F2	F3	F4
F1	Usefulness	3.997	0.690	**0.771**			
F2	Anxiety	2.280	0.910	−0.372	**0.732**		
F3	Expectancy	4.192	0.770	0.802	−0.323	**0.806**	
F4	Competency	3.189	0.890	0.491	−0.200	0.451	**0.780**

Note: Boldface in the diagonal line shows square root of AVE of each construct. Correlation is significant at the 0.01 level.

GenAI, with higher mean scores indicating greater confidence in their abilities to work with these technologies.

In the CFA sample, perceptions of usefulness were moderately high (M = 3.997), indicating that participants generally regarded GenAI technologies as beneficial tools. Regarding anxiety, the average score was slightly above the midpoint of the scale, suggesting a modest level of unease when engaging with these technologies. The expectancy dimension yielded the highest mean value among all factors, reflecting participants' strong optimism about the future role and integration of GenAI. In contrast, competency received the lowest mean score, pointing to comparatively lower self-assessed ability in using these tools. This combination of high expectancy and modest competency aligns with recent findings in GenAI-supported learning (e.g., Chan and Hu 2023; Yilmaz et al. 2023) and suggests that structured instructional support may be beneficial.

There are two methods to approach scale development: selecting questions based on theory or empirical data (Mc Dowell 2006). A major drawback of the empirical approach is that it can be challenging to understand why different results are often obtained for participants who respond to a question in a particular way. The theoretical approach involves choosing questions deemed pertinent from the perspective of a specific theory. Over the past several decades, theoretically derived instruments have become more and more popular in social research (Streiner et al. 2015). In this study, the scale development process was guided by constructs drawn from four theoretical traditions—TPB, TAM, SIT and DIT—each contributing a different lens for understanding attitudes towards GenAI. Rather than treating these theories as interchangeable or additive, their complementary roles were specified: TAM contributes cognitive evaluations (e.g., usefulness), TPB highlights motivational and affective elements (e.g., reservations or concerns), DIT provides a temporal–future-oriented lens (e.g., expectancy) and SIT informs self-perception and group-related confidence (e.g., competency). This conceptual integration clarified which constructs were relevant at the attitudinal level and guided the initial item pool. By grounding SAGAI in multiple theoretical traditions, this study offers an integrated perspective that explains both positive drivers (usefulness, expectancy) and barriers (anxiety, limited competency).

Accordingly, the four factors identified empirically correspond to theoretically anticipated attitudinal features rather than attempting to represent every construct of each theory. For example, TAM suggests that the two main determinants of technology adoption are perceived usefulness and ease of use. Usefulness items therefore reflect cognitive evaluations of GenAI's value in academic tasks.

TBP suggests that individuals' behaviour is influenced by their intentions and that these intentions are shaped by attitudes, subjective norms and perceived behavioural control. In SAGAI, the relevance of TPB appears in the anxiety factor, which reflects affect-based attitudinal hesitations that precede behavioural intention. The anxiety dimension of SAGAI addresses possible worries and fears that may affect individuals' intentions to use GenAI technologies, assessing concerns about the potential dangers and unethical uses of GenAI. If individuals perceive GenAI technologies as dangerous or unethical, this may negatively affect their intentions to adopt the technology, which in turn may reduce their overall behavioural intentions towards GenAI, in line with the attitude component of the TPB.

The items that come together under the *expectancy* dimension measure the long-term value and future projections of GenAI technologies, drawing on DIT. DIT is used here not to model diffusion but to conceptualise future-oriented attitudes towards GenAI's presence in education. This dimension of SAGAI also examines individuals' expectations about the importance and future presence of GenAI in education.

Finally, the analyses revealed that the dimension called *competency*, as a combination of three items, measures individuals' self-efficacy in using GenAI technologies and how competent they feel about it. SIT provides the theoretical foundation for understanding this dimension by highlighting how perceived belonging to technologically skilled groups shapes confidence and perceived capability. Self-confidence is captured in SIT through the degree to which individuals identify with their groups and the status of these groups. If a group has a high status and individuals feel that they belong to this group, this may increase their self-esteem. The achievements and positive characteristics of identified groups contribute to individual self-esteem and self-confidence. Likewise, the shared achievements of individuals in a group and positive relationships within the group can also strengthen individuals' self-confidence. In this context, individuals' perception of being a member of a technology group (e.g., 'tech enthusiasts' or 'digital natives'), according to SIT, means that they are more knowledgeable about GenAI technologies and feel more competent in using these technologies.

Chan and Hu (2023) advocate that by measuring and analysing student perceptions and concerns, policy makers can create data-driven guidelines and strategies for responsible and effective implementation of GenAI technologies. Building on this perspective, recent studies in AI-assisted language learning provide empirical support for the multidimensional structure of SAGAI. For example, Wang et al. (2025) show that classroom climate, AI literacy and resilience significantly predict student engagement in AI-mediated Chinese EFL classrooms, indicating that emotional and environmental conditions shape learners' willingness to use AI tools effectively. Their findings highlight that AI literacy increases both confidence and active participation, which corresponds to SAGAI's competency and usefulness dimensions. Similarly, Cui et al. (2025) demonstrate that perceived affordances of ChatGPT—such as actionable feedback, interactivity and adaptiveness—are strong predictors of motivated learning behaviour in AI-supported out-of-class language learning contexts. These results align with SAGAI's usefulness and expectancy dimensions, as students tend to adopt GenAI more positively when they perceive functional benefits and future value. Collectively, these studies reinforce the relevance of SAGAI's multidimensional approach by showing that emotional, cognitive, and capability-related factors jointly influence GenAI experiences. While the present study does not directly test interventions, SAGAI may serve as a diagnostic tool to identify areas where learners feel confident or hesitant, which can inform instructional design and support needs. However, the use of SAGAI for intervention planning should be approached cautiously, and additional empirical work is necessary to determine its effectiveness.

In practice, the scale can inform curriculum design, guide faculty training, and help policymakers monitor readiness for responsible GenAI adoption. For example, institutions can use SAGAI scores diagnostically to identify whether low competency or high anxiety is the stronger barrier in a given context. Such interventions can be seen as part of a holistic approach to maximising the potential of GenAI in education.

The rise of GenAI in the education sector is shaping teaching and learning methodologies, the assessment of student performance and the development of educational materials. SAGAI was developed to measure how this technological advancement is perceived and adopted in education. While SAGAI offers a structured way to examine student attitudes towards GenAI, its results should not be taken as direct predictors of performance or policy outcomes. Instead, the instrument provides a foundation for future research on GenAI readiness, learner perceptions and instructional design. SAGAI was developed in response to the growing significance of GenAI in education and, in this context, offers valuable insights to support educational institutions in adopting this emerging technological capability. It can serve as a foundational resource for both evaluating the current landscape and planning for future developments. Overall, SAGAI contributes an initial step towards understanding attitudinal responses to GenAI in higher education, but further studies using diverse samples and longitudinal designs are necessary to refine its applicability and examine its broader implications.

6.1 | Limitations & Future Research

The data used in this research were collected at two relatively homogenous, mid-sized public universities. Therefore, given that the findings represent only a specific demographic group (e.g., students of a certain age range, disciplines and cultural backgrounds), caution is warranted regarding the generalisability of the results. It is advisable to expand the sample to include different age groups, education levels and cultures.

Another limitation concerns the use of a single dataset for both EFA and CFA. Although this approach is widely applied in scale development studies (DeVellis 2017; Hinkin 1998), it may restrict the generalisability of the results. Nevertheless, prior methodological literature suggests that when the initial sample is sufficiently large, it is possible to randomly split the dataset into two halves and perform EFA and CFA on parallel subsamples (Krzystofiak et al. 1988). This strategy, which we adopted, is considered an acceptable and frequently preferred practice in instrument development, ensuring both exploratory and confirmatory validation within the same study design.

In this study, the participants were informed (subject to a brief orientation) about the text generation abilities of GenAI technologies. It is well known that GenAI is capable of much more, including multimedia production such as videos, audio and photographs. Due to the already high volume of items in the scale requiring participant time and the extensive duration that would be needed to test all such additional capabilities, it was not practical to incorporate any beyond text generation. Moreover, for a scale to remain practical, it should be administrable efficiently and within a short time frame. It is our aspiration to work on an extension of the scale to address this in the future. The continuous evolution of GenAI technologies may require SAGAI to be updated over time, but this will also provide researchers with a dynamism that will allow them to stay up to date in their fields. In this way, SAGAI can serve not only as a measurement tool but also as a reference point for development and adaptation in line with technological advancements. This is not a limitation of the scale, but rather an advantage in contributing to research and practice. Since culture is known to have different effects on various factors such as technology use and perceptions, it is recommended to verify the validity and reliability of the SAGAI in different cultural contexts. It is also recommended that this scale be adapted to English and other languages to examine cross-cultural differences, thus making it more universal.

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Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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Supporting Information

Additional supporting information can be found online in the Supporting Information section. **Appendix S1:** ejed70415-sup-0001-AppendixS1.docx. **Appendix S2:** ejed70415-sup-0002-AppendixS2.docx.