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Research article

Exploring pre-service teachers' generative AI readiness and behavioral intentions: A pilot study

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Abstract: Generative Artificial Intelligence (GenAI) has rapidly emerged as a field capable of creating unique content across various areas. While offering significant potential, it presents challenges including ethical concerns, content inaccuracies, and increased challenges for educators who must adapt to fast-evolving technologies. Integrating GenAI tools into teacher education represents an urgent global research priority. This pilot study explores GenAI readiness, experiences, perceptions, and behavioral intentions among Finnish pre-service teachers while examining the feasibility of the *GenAI Readiness Scale* as a measurement instrument. Using a mixed-methods approach combining quantitative survey data (N=77) with qualitative responses (n=56) from open-ended questions, the research provides a nuanced analysis of future educators' positioning toward GenAI integration in educational settings. Findings reveal a significant adoption gap, with 27% of participants never used GenAI tools as of April-June 2024, while majority engaged sporadically. Despite low perceived accuracy, frequent users continued utilizing GenAI, suggesting that usability, efficiency, and creative support outweigh accuracy concerns. Ideation and content creation emerged as the most common GenAI-supported tasks, while self-regulated and adaptive learning remained underutilized, indicating limited awareness of GenAI's broader potential. Challenges primarily involved output quality and prompting difficulties. Participants preferred modifying AI outputs rather than refining prompts, employing strategies like output modification and external verification, though critical evaluation wasn't always explicit. These findings highlight the need for structured AI literacy training in teacher education, emphasizing prompt engineering, evaluative judgment, and strategic AI integration. This study underscores the importance of developing GenAI competencies among pre-service teachers to ensure effective, responsible, and pedagogically meaningful AI adoption. Future research should explore longitudinal adoption trends, and impact of AI literacy training on teaching and learning practices.

Keywords: generative AI, teacher education, preservice teacher, technological adoption

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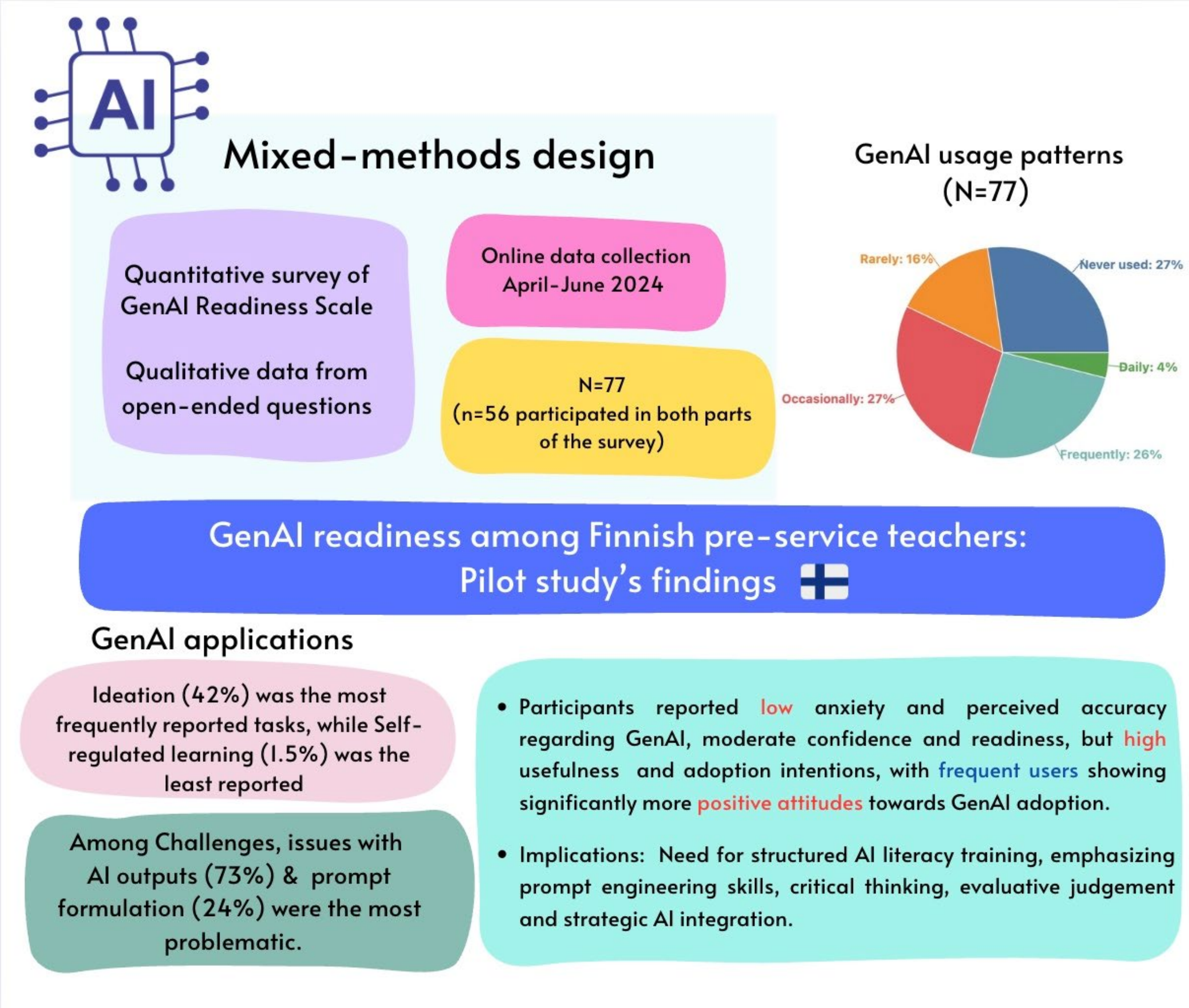


1 Introduction

We are living in an era where technological advancements continually redefine the boundaries of education. Among these, Generative Artificial Intelligence (GenAI) has emerged as a groundbreaking development, significantly transforming educational practices and reshaping how educators and learners interact with technology. GenAI utilizes sophisticated "foundational models" like Generative Pretrained Transformers (e.g., GPT-3, GPT-4) to create original content across various formats, including text, images, and software code (Bommasani et al., 2021). These tools are designed to assist users in tasks ranging from answering questions and generating creative writing to producing programming scripts and visual assets. For example, ChatGPT by OpenAI (OpenAI, 2024) is the most globally popular GenAI tool (Liu & Wang, 2024), enables users to engage in natural and informative conversations, brainstorm ideas, or even draft documents efficiently, making it a versatile assistant for both personal and professional needs (Aydın & Karaarslan, 2022; Lo et al., 2024; Mai et al., 2024). However, GenAI tools in educational contexts raise complex challenges, including concerns about academic integrity, ethical considerations, and the potential for misuse (Law, 2024; Lim et al., 2023).

Teachers and researchers are becoming progressively more aware of both the opportunities and challenges introduced by GenAI tools. On one hand, these tools hold immense potential to transform teaching practices and enhance student engagement (Law, 2024; Lo et al., 2024), and teachers generally have positive attitude towards GenAI (Kaplan-Rakowski et al., 2023). On the other hand, implementing GenAI tools in educational contexts raises unique challenges, such as ensuring ethical usage (Lim et al., 2023), navigating uncertainties (Bui et al., 2024; Parra et al., 2024) and long-term impact on pedagogical practices (Getenet, 2024; Mishra et al., 2023). As the influence and development of Gen AI continues to grow, educators are tasked with balancing its innovative capabilities with the responsibility of fostering critical, ethical, and purposeful use within their working environments (Kaplan-Rakowski et al., 2023; Law, 2024; Mai et al., 2024).

A recent report by World Bank released in September 2024 (Liu & Wang, 2024) tracked the top 40 GenAI tools, which received nearly three billion monthly visits from hundreds of millions of users from all over the world. As these advancements in GenAI continue to unfold, eliminating its use in education is neither practical nor desirable. The growing global engagement with GenAI highlights the need to understand these tools and their potential impacts in learning and teaching, as they rapidly transform the way information and knowledge is accessed, transferred and applied.

Global higher-education institutions and governments have quickly responded and issued their guidelines on the use of AI in education. For instance, the European Commission (2022) proposed that one of the core components in successfully integrating and harnessing AI systems in education is to increase educators' and teachers' AI competencies. Given these global initiatives, a critical question emerges: *How can we effectively prepare future teachers to engage with Gen AI tools in educational settings?*

As GenAI technologies have become increasingly popular, preparing future teachers is no longer optional but necessary to equip them with the critical skills and confidence to navigate these transformative tools. This preparation involves not only developing technical competencies, but also understanding their readiness and behavioural intentions towards GenAI. While current research increasingly explores Gen AI in education, there remains limited empirical evidence specifically focused on pre-service teachers' preparedness to engage with Gen AI technologies in their future professional practice (Moorhouse, 2024).

This pilot study provides initial insights into Finnish pre-service teachers' readiness, experiences, perceptions, and behavioural intentions regarding GenAI use in teaching and learning. It also explores the feasibility of the GenAI Readiness Scale as a measurement instrument. To address these aims, the study is structured into four interconnected sections. The theoretical framework guiding this work integrates current understandings of GenAI's unique characteristics in educational contexts with established behavioural intention theories, offering complementary perspectives on both the technological and psychological dimensions of technology adoption among pre-service teachers. Employing a mixed-methods approach, we combine quantitative measures of readiness with qualitative accounts of participants' experiences to gain a more comprehensive understanding of how measured readiness corresponds to self-reported perceptions. The integrated findings illuminate these relationships, while the discussion considers implications for teacher education practice. Although exploratory, this study lays important groundwork for refining research instruments and informing future large-scale investigations into GenAI integration in teacher education.

2 Research background

2.1 Generative AI in education

One thing that sets GenAI technology apart from earlier AI systems is its flexibility and adaptability that allow users to use natural language to engage with these tools. It is possible due to "foundational models" (Bommasani et al., 2021), such as Large Language Models (LLMs), which can be fine-tuned to handle diverse tasks. GenAI tools leverage vast datasets and machine learning techniques to simulate human-like decision-making and content creation processes, offering numerous potential applications such as language translation, tutoring, content generation, and personalized learning (Bommasani et al., 2021). At the core, GenAI is deep learning models - complex algorithms that mimic human learning and decision-making processes (Stryker & Scapicchio, 2024). These models utilize extensive parameters and training data, and can be guided by natural language prompts to accomplish tasks, even if they were not explicitly trained for them (Brown et al., 2022).

Their exceptional potential comes from a blend of model flexibility (adaptability in their input/output), generality (versatility across diverse tasks) and originality (capacity to produce novel content) (Schellaert et al., 2023; Tankelevitch et al., 2024). This unique combination of features makes them superior compared to previous digital tools, such as digital assistants, which are often bound to their limited task repertoires (Schellaert et al., 2023). As discussed in Bommasani et al., (2021), foundational models can be understood through their two key characteristics: **emergence** and **homogenization**.

Emergence refers to how these foundational models demonstrate capabilities and behaviors that were not explicitly programmed or trained, but instead "emerge" naturally from the scale and complexity of the data and training processes involved. For instance, ChatGPT is a pre-trained LLM developed by OpenAI Limited Partnership, San Francisco, USA (OpenAI, 2024) - demonstrates exceptional fluency and proficiency across a wide range of language-related tasks, allowing it to interpret and respond to diverse requests well beyond its initial design.

In educational context, when ChatGPT being used strategically, it can offer engaging and interactive personalized learning experience (Lo et al., 2024), even in areas like mathematics education (Bui et al., 2024). Unlike previous rule-based digital assistants that operating on pre-determined rules and pre-defined “if-then” guidance (Oxman et al., 2014), ChatGPT’s ability in understanding context and retaining information allows it to engage with users in a dynamic manner. Instead of scripted responses (Okonkwo & Ade-Ibijola, 2021), they can provide tailored and personalized answers and feedback (Law, 2024; Lo et al., 2024), step-by-step suggestions for problem-solving that encourage critical thinking (Hodge-zickerman & York, 2024; Li et al., 2023).

Homogenization highlights how foundational models standardize the methods used across various applications, leading to versatile models that are effective across many tasks. This means foundation models create a uniform approach in AI model design and architecture. Instead of building models for each purpose, it is possible to use a versatile model (i.e. GPT-4) that can be adapted and fine-tuned to address specific tasks, resulting in a more uniform model design and architecture across AI systems. For instance, Latif and Zhai (2024) demonstrated the effectiveness of fine-tuning ChatGPT (GPT-3.5) in automatically scoring students’ responses in science education (Latif & Zhai, 2024). Similarly, Nguyen et al., (2023) examined ChatGPT’s capacity in supporting teachers in grading and providing feedback on students ‘self-explanation for problem solving works in a math game named “Decimal Point” (Nguyen et al., 2023). Scoring students’ works is time-consuming and labor-intensive, especially during peak examination periods. These studies have highlighted the potential of fine-tuning AI models for educational applications.

These unexpected capabilities that arise naturally (emergence) and the efficiency and standardization these foundational models bring to AI development across various uses (homogenization) have expanded the development of AI as a field, they also bring forth unique challenges. For instance, the emergent behaviors Gen AI tools, though powerful, can be unpredictable, leading to concerns about unintended consequences or misuse, particularly in sensitive fields such as in education.

The phenomenon when GenAI chatbots “hallucinate” and provide made-up information or fake citations with absolute certainty (Haman & Školník, 2023) is one of the biggest concerns. Various cases have been recorded in different educational areas (Botana & Recio, 2024; Mai et al., 2024). Similarly, the **homogenization effect**—where a single foundational model can be adapted for many applications—also means that vulnerabilities or biases from one model could express across multiple use cases. This creates something called “single point of failure” where weaknesses in the foundational model can impact all systems relying on it (Bommasani et al., 2021).

GenAI’s performance can vary significantly depending on factors like how the prompt is formulated, the model’s capabilities, the presence (or absence) of specific training data. This means both positive outcomes and unexpected errors can appear without clear reasons, making the interpretation of generated contents even more complicated. Because of that, GenAI tools are considered highly user-dependent (Schellaert et al., 2023), which highlight the critical role of users' readiness in using GenAI tools.

2.2 Behavioral intentions and attitudes towards emerging technology

Technology integration in educational settings has evolved dramatically since computers became popular at schools in the 1980s (Parker & Davey, 2014). From basic instructional tools with singular functions to sophisticated, adaptive learning systems, technological innovations have consistently reshaped teaching and learning practices. The advent of GenAI represents a paradigm shift. Its complexity and wide-ranging potential of GenAI set it apart from previous disruptive technologies. For instance, the introduction of calculators had significantly impacted mathematics education (Lodge et al., 2023) as a basic function tool with well-defined purposes to simplify computations. GenAI tools, on the other hand, are not bound to a single discipline or pre-defined task repertoires (Bommasani et al., 2021). Their capacities to generate original content, automate administrative tasks, or be fine-tuned to facilitate specific tasks across various domains makes their implications for education highly significant.

Teachers' interaction and engagement with AI technology has been a topic of research relatively recently with the earliest studies where teachers' active involvement with AI in 2004 (Celik et al., 2022). However, majority of current research focus on AI as a predictor or indicator of academic performance, or the design of AI curriculum (Martin et al., 2024). The lack of teachers' perspectives from the discussions on the design, or implementation of AI in educational contexts is a significant concern that limits the practical relevance and adoption of these technologies (Celik et al., 2022; Martin et al., 2024). As the primary users of AI tools in classrooms, teachers bring invaluable insights into the practical challenges, pedagogical opportunities, and ethical considerations associated with integrating AI into teaching and learning in authentic settings. This underscores the need to understand educators' behavioural intentions, readiness and attitudes toward adopting emerging technology, as these factors are pivotal in determining the success in adoption of such technologies into realities of classroom practice (Kaplan-Rakowski et al., 2023; Martin et al., 2024).

While the perspectives of practicing teachers are important, pre-service teachers represent an equally significant yet often underexplored group. As future educators, they are uniquely positioned at the forefront of integrating emerging technologies into their practices (student) and future classrooms (teacher), sometimes they might be struggling conceptually between these two roles (Wang, 2002). Their dual roles as learners and future practitioners makes it essential to understand their perspectives as they are influenced not only by their own experiences but also by the training they receive during their preparation (Ottenbreit-Leftwich et al., 2010; Van Katwijk et al., 2023; Van Twillert et al., 2020; Ye et al., 2021).

Research by Farjon et al., (2019) examined the technology integration of 398 Dutch pre-service teachers at the start of their training program, and results showed that attitudes and beliefs significantly influenced their readiness to integrate technology, while access to technology had the least impact. Additionally, prior studies also suggested that novice teachers feel underprepared to address technological challenges they encounter in their professional positions (Farjon et al., 2019; Tondeur et al., 2012, 2016).

This perspective becomes more significant with the emergence of GenAI, which represents a distinct departure from previous educational technologies. Unlike earlier tools that were often introduced to students during formal training programs (Farjon et al., 2019; Tondeur et al., 2012; Wang, 2002), GenAI technologies - such as ChatGPT - have been made widely accessible to the general public since late 2022 (OpenAI, 2024). This accessibility has driven rapid adoption by students of all levels, often outpacing teachers' familiarity with these (Liu & Wang, 2024; Mai et al., 2024). This creates a unique dynamic for pre-service teachers, who must now navigate not only how to effectively use these tools but also how to manage their students' advanced use of them. This underscores the importance of understanding how pre-service teachers perceive GenAI, as well as their readiness and behavioural intentions, given their vital role shaping the future success of technology integration in education.

This study has an exploratory nature as it is driven by the limited literature available in this emerging field at the time of research. Specifically, we seek to address the following research questions:

1. What is the current level of GenAI readiness, behavioural intentions, perceptions and attitudes of pre-service teachers in Finland toward the integration of Gen AI technologies in the classroom?
2. In what ways are pre-service teachers in Finland utilizing GenAI tools in their learning and teaching practices?
    a. What challenges do they face when using GenAI tools?
    b. How do they manage or address these challenges?
    c. How do they engage with and utilize the outputs generated by GenAI tools?

3 Research methodology

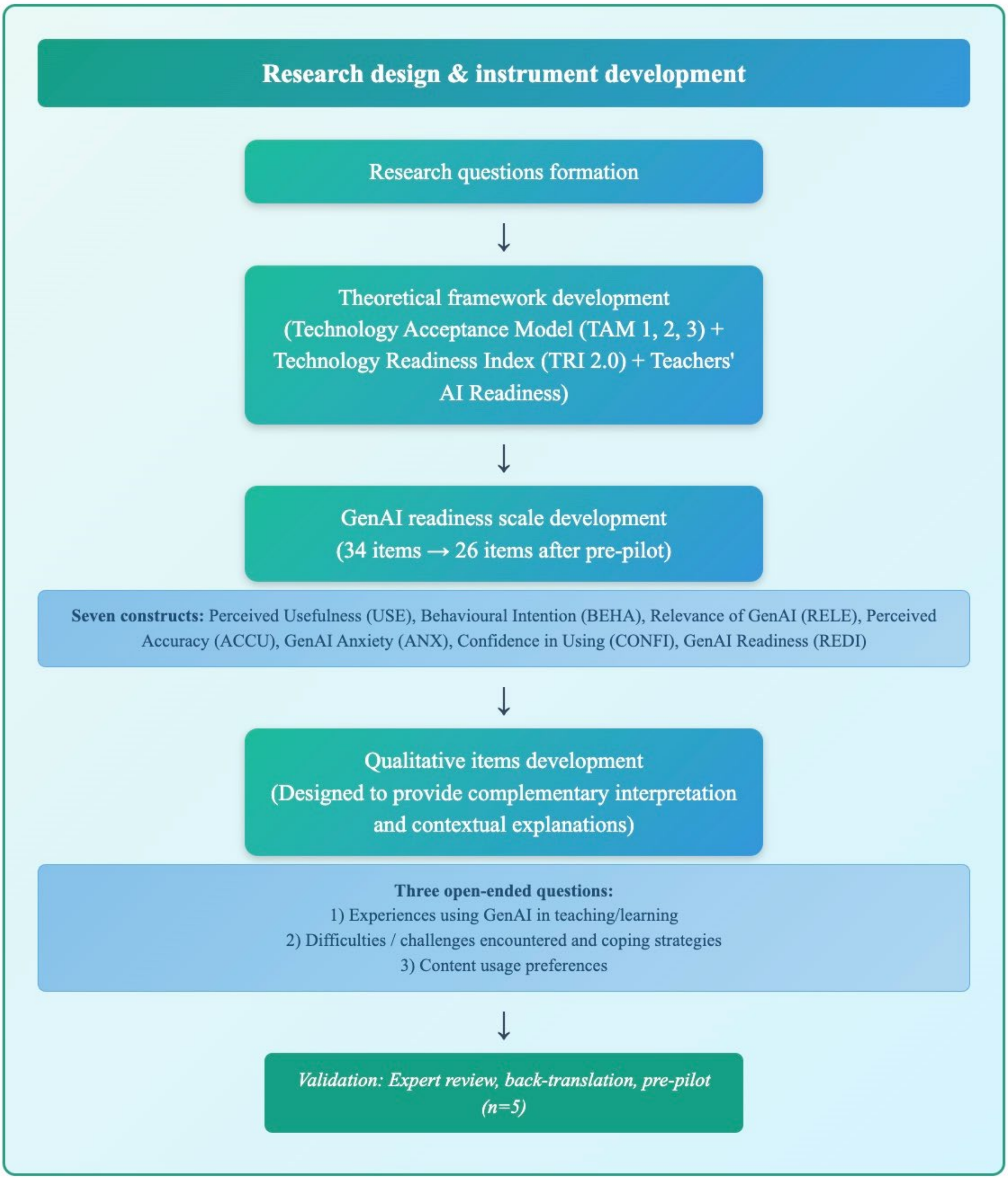
3.1 Research design and data collection

This study employed a mix-methods approach to examine Gen AI readiness, experiences, behavioural intentions, and perceptions of Finnish pre-service teachers. An online survey with two parts was developed and administrated through Webropol – a web-based survey platform. The first part collected background information, and contained questions related to participants' usages of Gen AI tools. Participants who had never used GenAI (n=21) were not directed to the second part. The second part included the Gen AI Readiness Scale (see 3.3.), and three open-ended questions as following:

1) *Please describe any experiences you have had using GenAI in your teaching or learning activities. What was the context, and what were the outcomes?*
2) *What difficulties or challenges have you encountered when using GenAI in your teaching or learning activities? How did you address these challenges?*
3) *Do you typically use the content directly generated by Gen AI tools, or do you prefer to modify and take ownership of the content? Please explain your approach.*

Participants had the option to skip the open-ended questions. The first question received 86% response rate (n=48), the second had 66% (n=37), and the last one achieved 98% response rate (n=55). The link to the survey were emailed to the participants. Participants were provided with all the essential information related to the research, contact personnel and how collected data would be processed, stored and managed. The survey was distributed to students via the official communication channels of various member associations within the Teacher Student Union of Finland. The voluntary nature of participation may partly explain the low response rate. The link to questionnaire remained open for responses from late April to June 10th, 2024.

Figure 1. Research design and instrument development of the study



3.2 Participants

A total of 77 (n=57 female, n=15 male, n=5 not disclose) Finnish pre-service teachers responded to the survey, of which 56 answered both parts of the questionnaire. Majority of respondents belonged to the age-group 21-24 (41.5%). Class Teacher students represent the largest group (59.7%), following by those belong to Subject Teacher major(s) (50.6%) and Early Childhood Education (20.8%).

3.3 Instrument design

The development of GenAI Readiness scale is informed by and adapted from prior validated instruments, while also taking into consideration the unique characteristics of foundational models in GenAI (see Figure 1). The instrument expands cross seven constructs (see Appendix A). The following section outlines the design process for the constructs of the instrument.

Perceived usefulness

The foundational framework of the scale is adapted based on the Technology Acceptance Model (TAM 1, 2, 3) (Davis, 1989; Venkatesh & Bala, 2008; Venkatesh & Davis, 2000). Although TAM was originally developed in and for working environment contexts, its constructs have also been applied successfully to educational contexts where pre-service teachers must decide whether or not to embrace new emerging technologies such as floor-robots or virtual reality headsets (Casey et al., 2021, 2023). TAM 1 introduced two key constructs: Perceived Usefulness and Perceived Ease of Use, which have been theorized to predict individuals' adoption (Behavioural Intentions) and use of new technologies (Use Behaviour) in a work environment (Casey et al., 2023).

Perceived Usefulness has been shown to be an important factor in predicting behavioural intention of teachers in integrating AI in schools (Ayanwale et al., 2022; Darmansyah et al., 2021). In line with the TAM framework, we posit that when pre-service teachers find Gen AI technology useful for their learning and teaching tasks, it enhances their overall readiness to adopt these tools. For the items measuring Perceived Usefulness of Gen AI, we adapted elements from TAM (Davis, 1989), incorporated insights from related studies (Ayanwale et al., 2022; Casey et al., 2021) and considered the unique characteristics of Gen AI tools.

Behavioural intention

Behavioural Intention is also built on the foundational TAM framework (Davis, 1989), which measured users' intention to incorporate technological tools in their tasks. In this case, it means pre-service teachers' intention towards Gen AI's integration into their learning and teaching practices. As Perceived Usefulness is theorized to influence pre-service teachers' decision in adopting GenAI tools, we also believed Behavioural Intention is an important construct.

Relevance of Gen AI

TAM 2 expanded on the original model by incorporating external variables that theorized to influence Perceived Usefulness, including Subjective Norm, Image, Job Relevance, Output Quality and Result Demonstrability (Venkatesh & Davis, 2000). Among these determinants, Job Relevance of new technologies to one's professional tasks plays a significant role in shaping technology acceptance. Venkatesh & Davis (2000) defined Job Relevance as "*The degree to which an individual believes that the target system is applicable to his or her job*".

In the context of pre-service teachers, Job Relevance becomes critical as these individuals are in the formative stages of their professional development. Dai et al., (2020)'s findings indicated that students' perception of AI readiness is shaped by their confidence in their ability to learn and utilize AI knowledge, along with their understanding of how AI aligns with and is relevant to their current and future lives. Similarly, Ayanwale et al., (2022) also found that AI relevance predicted both teachers' readiness and behavior intention towards AI integration. Hence, we incorporated the Relevance of Gen AI construct to examine pre-service teachers' perceptions in this context.

Perceived accuracy of Gen AI

According to Venkatesh & Davis (2000), the higher the quality of the tool's output, the stronger the effect it has on perceived usefulness. Output Quality is defined as "The degree to which an individual believes that the system performs his or her job tasks well", measured with items such as: "*The quality of the output I get from the system is high*" (Venkatesh & Davis, 2000). With GenAI, this conceptualization does not fully capture the characteristic and complexity these tools. GenAI tools are fundamentally different with prior technologies studied under TAM frameworks, such as computer applications to monitor stock portfolios or operational systems (Venkatesh & Bala, 2008). These applications were specifically designed to excel within their limited task repertoires. In contrast, GenAI can generate novel, dynamic content and accomplish tasks they were not explicitly trained to perform (Bommasani et al., 2021; Brown et al., 2022), and their outputs can be unpredictable, making Gen AI tools highly user-dependent (Schellaert et al., 2023).

This characteristic introduces unique considerations from users' perspectives, such as their perceived accuracy and consistency of GenAI-generated outputs, which are critical for understanding their behavioural intentions. Research highlighted the importance of addressing concerns related to AI-generated content, especially when Gen AI tools have been reported to be inconsistent, or making up citations and information with certainty (Haman & Školník, 2023; Mai et al., 2024; Manohar et al., 2024). Mehrabi et al., (2022) discussed the challenges of biases and inconsistencies in AI outputs, which directly influence users' trust and willingness to integrate such technologies. Hence, we incorporated the construct Perceived Accuracy of GenAI to examine pre-service teachers' perceptions of Gen AI tools' ability to produce reliable content.

While Output Quality focuses on the general effectiveness of a system, Perceived Accuracy extends to specific concerns, including biases, fairness, and the need for verification. Importantly, our conceptualization of Perceived Accuracy encompasses both perceptions of trustworthiness and the resulting verification behavior, which we believe is an intrinsic component of how users relate to GenAI outputs rather than a separate construct. This integration is supported by trust-verification theories (Lee & See, 2004), which posit that verification behavior is a natural consequence of uncertainty about system reliability, particularly in contexts like education. These items were designed to capture participants' perceptions of the accuracy, reliability, and consistency of GenAI-generated output, while also acknowledging concerns about potential biases and their intent to critically evaluate content before use.

Gen AI anxiety

Even when technologies are perceived as useful and relevant, certain psychological barriers can hinder its adoption. These barriers, such as Computer Self-Efficacy, Computer Anxiety, Objective Usability, were addressed in TAM 3 (Venkatesh & Bala, 2008). Anxiety is referred as the apprehension or fear experienced when an individual is faced with the use of computer (Venkatesh & Davis, 2000). In AI-adoption literature, a similar concept has been discussed is AI Anxiety. While conceptually related to computer anxiety, these two are not the same. Li & Huang (2020) identified eight dimensions of AI anxiety based on integrated fear acquisition, including privacy violation, bias behavior, job replacement, learning anxiety, existential risk, ethics violation, artificial consciousness and lack of transparency anxiety (Li & Huang, 2020).

GenAI technology is new and rapidly evolving, which could be intimidating. Anxiety related to GenAI becomes critical as pre-service teachers are simultaneously navigating professional training and developing their identities as educators (Wang, 2002). This dual role may lead to increased stress about keeping up with GenAI advancements, concerns over job security, and potential challenges these technologies may pose in their teaching practice. Recognize this, the inclusion of GenAI Anxiety construct in this study is essential for understanding how psychological barriers may affect pre-service teachers' acceptance and use of AI tools. Based on related literature (Ayanwale et al., 2022; Li & Huang, 2020), we incorporated items to capture these concerns through Gen AI Anxiety construct.

Confidence in using Gen AI

In contrast to anxiety, another factor was discussed in TAM 3 is Computer Self-Efficacy (Venkatesh & Bala, 2008). Self-efficacy is broadly defined as an individual's belief in their capacity to successfully perform specific tasks (Bandura, 1997). In the context of technology adoption, computer self-efficacy refers to one's confidence in their ability to effectively use computer systems or software to accomplish their tasks, which plays a critical role in shaping users' behavioural intention (Venkatesh & Bala, 2008). Pre-service teachers often face unique pressures as they balance professional training with the challenges of preparing to meet the demands of 21st-century classrooms (Tondeur et al., 2012). Research suggested that teachers with higher confidence are more likely to adopt and experiment with new tools in their workplace while a lack of confidence lead to avoidance behaviours (Tondeur et al., 2017). Hence, we include Confidence in Using GenAI construct in our study (Ayanwale et al., 2022; Tondeur et al., 2017).

GenAI readiness

GenAI Readiness construct is conceptually based on the Technology Readiness Index (TRI 2.0) (Parasuraman & Colby, 2015). TRI 2.0 is designed to understand people's likelihood to exhibit a particular behavioural outlook toward technology based on readiness level. Ayanwale et al., (2022) conducted an empirical study to examine teachers' readiness, among other variables, to predict intention to teach AI in Nigerian K-12 classrooms context. Their findings suggested that AI readiness positively influenced on teachers' behavioural intentions to teach and promote AI-related activities. We therefore included the GenAI Readiness to examine pre-service teachers' preparedness in incorporating GenAI tools. We adapted elements from Ayanwale et al., (2022) with considerations of the unique characteristics of Gen AI tools.

3.4 Instrument development

First, an item pool consisted of 34 statements across seven constructs were developed. These statements were initially developed in English and reviewed by two educational science experts. After revisions, the list of items followed the recommended "back translation" method (Brislin, 1970) to Finnish language and back-translated to English by two bilingual Finnish native speakers. Then, the Finnish translated version was reviewed by two independent Finnish researchers.

A pre-pilot was conducted in March 2024 with five Finnish pre-service teachers, who completed the full questionnaire, including background and GenAI tool usage questions (part one), and 34 GenAI scale items plus three open-ended questions (part two). They provided written feedback on completion time, format, clarity, and ease of understanding.

Based on the feedback, the scale was revised to include 26 items across seven constructs: Perceived Usefulness (USE), Behavioural Intention (BEHA), Relevance of Gen AI (RELE), Perceived Accuracy (ACCU), Gen AI Anxiety (ANX), Confidence in Using (CONFI), and Gen AI Readiness (REDI). Participants were asked to rate the level of agreement on a Likert scale from 1 (Strongly disagree) to 6 (Strongly agree).

3.5 Data analysis

Quantitative data

Quantitative data were analysed using SPSS 28 software. Various statistical methods were employed, including descriptive statistics, t-test, reliability analysis. Cronbach's Alpha was calculated for the constructs of the GenAI Readiness scale (Table 1).

Table 1. Cronbach's α of seven constructs in the Gen AI Readiness Scale

Constructs	Items	Cronbach's α
ANX	3	0.612
USE	4	0.69
BEHA	3	0.85
REDI	4	0.77
RELE	4	0.75
ACC	4	0.612
CONFI	4	0.73

Most variables have acceptable reliability ($\alpha \geq 0.70$), with USE at a slightly lower level ($\alpha = 0.69$), except for ANX & ACCU ($\alpha = 0.61$), which indicates moderate internal consistency. Given the nature of this pilot study and the conceptualization of these constructs, especially with ACCU, as this construct was developed to reflect the unique nature of Gen AI tools based on limited available literature, these values are deemed sufficient for now. Factor analysis was not performed due to a small sample size (N=56) relative to the number of constructs (7), as research demonstrates that reliable factor recovery requires substantially larger samples (at least $N \geq 200$) when examining multiple factors, particularly for emerging constructs where psychometric properties are unknown (MacCallum et al., 1999).

Qualitative data

The qualitative data were imported into MAXQDA24 for manual coding and thematic analysis. Our approach aimed to identify key insights by allowing categories to emerge inductively from the data (Naeem et al., 2023). Simultaneously, we incorporated theoretical constructs and frameworks such as TAM 1,2,3 (Venkatesh & Bala, 2008; Venkatesh & Davis, 2000) identified during the development of the GenAI Readiness Scale to ensure a structured data extraction process and the consolidation of codes into coherent themes.

We first developed a two-dimensional coding scheme to classify the "Types of Tasks" in which participants used Gen AI. The first dimension sorted tasks based on their broader context (e.g., learning-related). The second dimension classified tasks by their functional purposes (e.g., ideation). Regarding the functional purpose, because one activity might serve different purposes, based on the context, each mention (or response) is assigned **a single best-fit category** to avoid overlapping.

Next, several coding themes emerged to classify participants' experiences. These included Positive Experiences, Negative Experiences, and Concerns. Positive Experiences includes sub-groups such as "Perceived Usefulness" (e.g., participants found Gen AI helpful in assisting with tasks) or "Usability and Productivity" (e.g., instances where Gen AI was perceived as easy, time-saving than other methods). Negative Experiences includes "Lack of Usefulness" (e.g. where Gen AI's performance did not meet participants' needs or expectations), while Concerns is formed with sub-groups such as “Ethical Concern” (e.g., concerns over ethical issues related to Gen AI use). Similarly to how we classify the purposes task, each mention or example under the same theme is assigned a single best-fit category to each sub-group to avoid overlapping.

Lastly, we developed coding categories to capture challenges and coping strategies of participant engagement with Gen AI outputs. Common challenges included “Prompt Refinement” (e.g., difficulties in crafting or refining prompts) or “AI-generated Outputs” (e.g., struggles with interpreting Gen AI-generated content). Corresponding to these were solution-oriented codes, such as “Modification of Outputs” (e.g., participants edited, refined, or adjusted AI-generated content to meet their needs) and “Future Intention” (e.g., participants planned to engage with Gen AI moving forward).

For a detailed coding structure and definitions, see Codebook Appendix.

4 Results

4.1 Pre-service teachers’ usage of GenAI tools

A portion of participants (27%) indicated that they Never used GenAI (n=21). Of those who indicated that they had used (n=56), 16% (n=12) using them Rarely, 27% (n=21) used Occasionally, while 26% (n=20) used them Frequently and 4% (n=3) reported Daily usage. Participants are grouped into two frequency groups: Low Frequency (Rarely + Occasionally) n=33 and High Frequency (Usually + Daily) n=23 for further analysis.

Regarding the types of Gen AI tools being used by participants, the overwhelming majority (98.2%) reported to have use OpenAI’s ChatGPT, following by DALL-E2 (18%) which is another Gen AI tool by OpenAI. Google Gemini (Bard) (11%) and Github Copilot at 9% followed respectively. Our results aligned with recent report about the domination of ChatGPT as the most popular Gen AI tool worldwide.

4.2 Pre-service teachers’ Gen AI readiness and behaviour intentions

Table 2. Descriptives statistics of Gen AI Readiness

Constructs	**N**	**Mean**	**SD**	**Skewness**	**Std. Error of Skewness**	**Kurtosis**	**Std. Error of Kurtosis**
ANX	56	2.7	0.96	0.16	0.319	-0.68	0.628
USE	56	4.3	0.80	-0.63	0.319	0.03	0.628
BEHA	56	4.0	1.1	-0.82	0.319	0.66	0.628
REDI	56	3.3	1.01	0.45	0.319	0.02	0.628
RELE	56	3.6	0.93	-0.22	0.319	0.48	0.628
ACC	56	2.6	0.73	0.31	0.319	-0.43	0.628
CONFI	56	3.8	0.78	0.11	0.319	0.23	0.628

Results (Table 2) suggested that participants showed relatively low anxiety regarding GenAI (M=2.7; SD=0.96), while they considered GenAI tools to be moderately useful (M=4.3; SD=0.78). Regarding GenAI relevance, participants expressed marginally above neutral level of relevance (M=3.6; SD=0.93). Participants reported to have clear intention to adopt and stay up-to-date on the development of GenAI technologies (M=4.0; SD=1.1), but their confidence in using these tools (M=3.8; SD=0.78) and level of self-reported readiness (M=3.3; SD=1.0) are moderate, with low perceived accuracy towards to content generated by Gen AI (M=2.6; SD=0.73).

To assess potential differences in participants' GenAI readiness based on their usage frequency, participants were divided into two groups: Low Frequency (n=33) and High Frequency (n=23). An independent t-test was conducted to examine the differences in six Gen AI Readiness constructs between these groups (Table 3), with the exception of ACCU, a Welch's t-test was applied due to unequal variances. There was no difference in perceived accuracy between two groups, $t(53.41) = -0.333$, $p = 0.740$.

Table 3. Gen AI Readiness t-test between frequency groups

	Low N=33	**High N=23**								**95% CI for Cohen's d**	
	M (SD)	**M (SD)**	**t**	**df**	**p**	**Mean Diff**	**SE Diff**	**Cohen's d**	**SE Cohen's d**	**Lower**	**Upper**
ANX	2.76 (0.99)	2.6 (0.93)	0.57	54	0.573	0.15	0.26	0.15	0.27	-0.38	0.69
USE	3.91 (0.73)	4.82 (0.56)	-4.96	54	<.001	-0.90	0.18	-1.35	0.32	-1.93	-0.75
BEHA	3.56 (1.1)	4.6 (0.8)	-3.65	54	<.001	-0.98	0.27	-0.99	0.30	-1.55	-0.42
REDI	2.88 (0.79)	3.94 (0.98)	-4.46	54	<.001	-1.06	0.24	-1.21	0.31	-1.79	-0.63
RELE	3.2 (0.86)	4.12 (0.74)	-4.25	54	<.001	-0.94	0.22	-1.15	0.30	-1.73	-0.58
CONFI	3.66 (0.75)	4.07 (0.79)	-1.99	54	0.051	-0.41	0.21	-0.54	0.28	-1.08	0.003

Results suggested that there was no significant difference in anxiety about GenAI technology between these groups, $t(54) = 0.567$, $p = 0.573$. However, significant differences with large effect sizes were observed for perceived usefulness $t(54) = -4.96$, $p < .001$, $d = -1.35$; behavioural intentions towards Gen AI technologies adoption $t(54) = -3.65$, $p < .001$, $d = -0.99$; relevance of GenAI tools $t(54) = -4.25$, $p < .001$, $d = -1.15$; and readiness towards the integration of GenAI in teaching and learning practices $t(54) = -4.46$, $p < .001$, $d = -1.21$. Concerning their confidence towards using GenAI, the difference approached significant at $t(54) = -1.99$, $p = 0.051$, with a medium effect size ($d = -0.541$).

4.3 Pre-service teachers' engagement with Gen AI Tools

Types of tasks

Table 4 presents the distribution of task types in which participants reported to use GenAI. These tasks are categorized based on functional purposes and contexts. As shown, Ideation (42%) and Lesson Planning & Material Design (20%) were the most frequently reported tasks, while Self-Regulated Learning (1.5%) was the least mentioned.

Table 4. Overview of Gen AI task types based on functions and context

Function-based tasks	Context-based tasks	Code segment examples	Frequency	%
Ideation (30 mentions) 42%	Learning	"It's great for generating ideas and even bringing new perspectives to studying."	15	21%
	Teaching	"I primarily use ChatGPT as inspiration for teaching, for example, asking for warm-up ideas for a topic."	3	4%
	General	"…ideas for meals, grocery lists"	12	17%
Summarization (9 mentions) 13%	Learning	"Gen AI tools have been convenient for summarizing exam materials."	8	11%
	General	"The most common use is to search for summaries of specific topics"	1	1.5%
Revision & verification (9 mentions) 13%	Learning	"I've used it to check if I've done my homework correctly or if AI arrives at similar solutions."	7	10%
	General	"Sometimes I find it difficult to articulate what I mean, and ChatGPT helps me phrase or finalize what I want to say."	2	3%
Lesson Planning and Material Design (14 mentions) 20%	Teaching	"I've also used AI tools to create questions and topics for students to write opinion about."	14	20%
Concept Exploration & Problem-Solving (8 mentions) 11%	Learning	"I've used AI for assistance when I've been stuck on tasks, whether in math or writing-related assignments. ChatGPT isn't very good at math, but it has helped me understand how to approach a problem."	8	11%
Self-regulated Learning (1 mention) 1.5%	Learning	"In one course, I used a study schedule, exercises, tasks, and materials created by ChatGPT to learn Python programming. During a 40-hour session, I learned Python basics, and the AI-made schedule was good and progressed at a suitable pace."	1	1.5%
Total mentions: 71				100%

Pre-service teachers' experiences with Gen AI tools

Participants' experiences with GenAI tools (Table 5) were categorized into Positive Experiences (39%), Negative Experiences (20%), and Concerns (41%). Perceived Usefulness (34%) dominated positive experiences, with Usability and Productivity noted marginally (5%). Negative experiences centred on Lack of Usefulness (20%). Concerns were the most varied, with Trust and Accuracy (28%) most frequently cited, followed by Ethical Concerns, Overreliance, Misuse, and Wrongful Use (4–6%), and AI Awareness (2%).

Table 5. Participants' experiences with Gen AI tools

Themes	**Sub-category**	**Code segment examples**	**Frequency**	**%**
Positive Experience (48 mentions) 39%	Perceived Usefulness	"I've used ChatGPT to support essay writing, mainly to get different perspectives when I couldn't come up with enough myself"	42	34%
	Usability and Productivity	"(...) By this, I mean a short summary of, for example, a theory I want to understand without having to look for the same information in books or articles."	6	5%
Negative Experience (25 mentions) 20%	Lack of Usefulness	"Gen AI doesn't always understand what I mean, so I have to spend a lot of time discussing with it, clarifying things, and questioning its incorrect answers."	25	20%
Concerns (50 mentions) 41%	Trust and Accuracy	"For example, in math, the numbers are often wrong. There can also be factual errors. Sometimes AI's answers are unnecessarily long, even when you ask for a short response."	34	28%
	Ethical Concerns	"(...) I don't like engaging with the current copyright culture around it (*AI-outputs*). It has also caused quite a bit of harm."	6	5%
	AI Misuse and Wrongful Use	"Despite restrictions, a student used AI to write their assignment. Students are already skilled at using AI, even in elementary school (level)"	4	3%
	AI Awareness	"(*Reliability is low. There is a lot of repetition. Bias is common*). These are things that should be taken into account and highlighted to students. AI is not really intelligent, nor does it know anything - it only guesses what is probable based on the data it has been trained on."	4	3%
	Overreliance in AI	"(*It's important for students to distinguish what is AI-generated*). In my opinion, it's difficult to get students to understand that AI is just a tool and shouldn't be fully relied upon."	2	2%
Total mentions: 123				100%

Results indicate Concerns emerged as the most frequently mentioned theme, with a particular focus on trust and accuracy issues regarding AI-generated outputs. These results support our quantitative data regarding participants' perceptions towards Gen AI's perceived accuracy, regardless of their frequency of Gen AI usage. Many participants expressed doubts about the reliability of AI responses, highlighting potential wrong information or inconsistencies. Despite these concerns, positive experiences were also widely reported, making them the second most common theme, which also evident in our quantitative data.

Pre-service teachers' experienced challenges and response strategies

Participants' challenges with GenAI tools and their responses were categorized into two main themes: Challenges and Solutions/Behavioural Intentions. Four participants reported no challenges, two due to limited GenAI use. Among Challenges, issues with AI-generated outputs (73%), prompt formulation (24%), and user competence (1%) were identified. In Solutions and Behavioural Intentions, five strategies emerged, with Output Modification (50%) most common, followed by External Verification and Critical Evaluation (20%), Prompt Refinement (8%), AI Use for Specific Tasks (8%), and Future Intentions (8%).

Table 6. Participants' challenges in using Gen AI tools and their response strategies

Themes	Sub-category	Code segment examples	Frequency	%
Challenges	AI-generated Outputs	"...but occasionally they (GenAI) include guesswork or made-up information presented in a convincing format."	27	73%
	Prompt Challenges	"AI doesn't always understand what is expected of it, so clarifying questions often need to be asked."	9	24%
	Competence	"The biggest problems I've faced with AI come from the fact that the other party (e.g., a colleague) doesn't understand enough about AI."	1	2%
Total mentions: 37				100%
Solutions & Behavioural Intentions	Modifications of Outputs	"I asked AI what relevant questions might exist on the topic. It gave me five different questions as a response. In the end, I chose one and refined it into a better form based on my own thoughts."	38	50%
	External Verification & Critical Evaluation	"You need to take AI outputs to the extreme with parameters and choose the gems instead of looking at its results as a complete".	16	20%
	AI for Specific Tasks	"I haven't created content with it; I've only used it as a tool to aid my own learning. For example, it's easy to double-check math problems yourself once AI shows the method to solve them."	8	11%
	Future Intentions	"A professor used AI to create illustrations for his course and AI-generated craft texts, which I also plan to use in teaching in some way."	8	11%
	Prompt Refinement	"I've created teaching materials for middle school math lessons using AI. The problem is that AI generates one-dimensional tasks and can't provide correct solutions to the problems. With more specific commands, you can get more versatile tasks, and the solutions can be created manually. "	6	8%
Total mentions: 76				100%

Findings reveal that AI-generated output issues were the most common challenge, followed by prompt-related difficulties. In response, participants primarily managed these challenges by modifying AI-generated outputs and externally verifying information or engaging in evaluative judgement, while fewer engaged in prompt modification to get better results, or restricted AI use to specific tasks. These results suggest that while participants recognize Gen AI's potential, they also acknowledge its limitations, relying on human oversight and critical evaluation rather than fully trusting AI-generated content.

5 Discussions

5.1 Pre-service teachers' Gen AI readiness and behavioral intentions

A notable 27% of participants never used GenAI tools at the time of the survey (April-June, 2024), while those who had reported varying usage frequencies. This reveals a significant gap in GenAI adoption among Finnish pre-service teachers, with most falling into the low-frequency category. However, a smaller yet substantial group reported regular use, suggesting that some are actively integrating Gen AI into their learning and teaching practices. These results align with broader trends reported by the U.S. Bureau of Economic Research (Bick et al., 2024), which suggested that higher adoption rates were observed among individuals with graduate degrees (40.9%) and STEM backgrounds (46%), whereas those in Liberal Arts and other non-STEM fields had lower adoption rates (22.4%). This indicates that structured AI literacy initiatives are necessary to ensure equitable technology integration, particularly for non-STEM and less experienced users, such as pre-service teachers.

Our results also show that high frequency participants see these tools as more useful, and are more likely to use them in the future. They find GenAI to be more relevant, and feel better prepared compared to those who use these tools less frequently. While high frequency participants reported feeling more confident in using GenAI, this difference in confidence between the two groups is not significant. This reinforces previous studies on AI adoption in education, which indicate that exposure and hands-on experience with AI tools correlate with more positive attitudes and higher adoption intentions (Wang et al., 2020). Participants who used Gen AI tools frequently saw them as more useful, relevant, and worth adopting, similar to prior research on technology acceptance, where perceived usefulness and ease of use drive adoption behaviors (Venkatesh & Bala, 2008).

Our findings suggest that frequency of use did not influence anxiety or perceptions of GenAI accuracy, which remained consistently low across all users. Our results indicate an interesting pattern in GenAI tool adoption, one that differs from prior technological integration models. Previously, the perceived quality of a technology's output has been a significant moderating factor in adoption and perceived usefulness (Kreijns et al., 2007; Venkatesh & Bala, 2008; Venkatesh & Davis, 2000). While our study does not measure Output Quality directly, the construct of Perceived Accuracy considers from users' assessments such as their perceived accuracy and consistency of GenAI-generated outputs. Interestingly, our results indicates that participants, regardless of their frequency usage, perceive GenAI outputs to be low in accuracy, yet frequent users continue to use these tools.

Moreover, despite this concern, participants generally reported finding Gen AI tools to be useful and indicated a high intention to use them in the future. This is further reinforced by our qualitative findings, with trust and accuracy emerged as the most frequently reported issues, and challenges related to GenAI-generated outputs being the most dominant problem in participants' responses; however, participants still find GenAI tools to be useful, efficient and used them for a wide variety of tasks in different contexts. This suggests that factors beyond perceived accuracy or output quality - such as usefulness, usability, efficiency, accessibility, or creative augmentation – may play a more crucial role in GenAI adoption.

It seems a fundamental shift in our relationship with AI technologies has emerged. While previous digital tools like computer software were valued primarily for their factual accuracy (Venkatesh & Bala, 2008), GenAI seems to be perceived differently by users. Rather than being judged as authoritative information sources, these systems are increasingly embraced as collaborative thinking partners, creative catalysts, and intellectual scaffolding for human thought. This reconceptualization aligns with the "Human-in-the-Loop" paradigm proposed by Puerta-Beldarrain and colleagues (Puerta-Beldarrain et al., 2025), which suggests that full trust in AI accuracy becomes less critical when users engage with these systems as co-creative partners in a dynamic, iterative process. The user becomes not merely a consumer of AI outputs but an active participant in a new form of augmented cognition.

Our findings challenge traditional assumptions about accuracy as one of the primary drivers of technology adoption (Wang et al., 2020). Despite low perceived accuracy, this suggests that frequent GenAI users continue using GenAI tools, indicating that trust in GenAI output is not the sole determinant of behavioral intentions. This aligns with research on human-AI collaboration models, where users act as critical evaluators rather than passive recipients of AI-generated content (Puerta-Beldarrain et al., 2025).

5.2 Patterns and task engagement in Gen AI use

Our qualitative analysis indicated that participants used GenAI tools across various tasks and contexts, with a strong preference for ideation tasks. Ideation was the only type applied across learning, teaching, and other contexts. Lesson planning and material design were popular and limited to teaching. Summarization and revision tasks were moderately used in both learning and teaching, while concept exploration, problem solving, and self-regulated learning were used only in learning and were least reported, especially self-regulated learning.

This suggests that while Gen AI is leveraged for exploring perspectives, content creation and instructional planning, it is not yet very widely used for self-directed learning, personalized feedback or independent skill development, which are often considered the most prominent strengths of Gen AI tools in education (Mittal et al., 2024). This gap may indicate a lack of awareness, confidence or training in using Gen AI for adaptive learning. This also highlights the need for teacher training programs to promote more targeted AI literacy initiatives for skill building, assessment and feedback, ensuring pre-service teachers have the capacity to explore and take advantage of Gen AI's full potential beyond quick content generation.

5.3 Challenges and coping strategies

Challenges in using Gen AI tools were predominantly related to AI-generated outputs, including issues with accuracy, relevance or coherence, followed by prompting related difficulties. In response, participants most commonly modified and edited outputs to fit with their needs, a strategy also observed in other studies where users engage in iterative refinement to improve AI-generated content (Puerta-Beldarrain et al., 2025; Tankelevitch et al., 2024). External verification and critical evaluation were another key strategy, in which participants cautiously used their judgement to cross-check AI-generated content with other sources, or applied personal judgement to assess reliability before proceeding with decision about using the content or not.

It is important to highlight that those reported to edit AI-generated outputs are not necessarily disengaging from critical evaluation. While we separated these two as separate coping strategies, based on the context and examples given by participants, they might simply not explicitly mention it, or be unaware that they are doing it. This could happen for two reasons. First, research on trust calibration in AI-supported decision-making suggests that users often engage in heuristic rather than systematic evaluation (Eisbach et al., 2023). This means their engagement may reflect implicit trust calibration, where users adjust AI outputs based on prior knowledge, while less confident users may either overrely on AI or reject it outright.

Second, prior knowledge plays a critical role in the evaluation process, as those with strong subject knowledge may engage in implicit evaluation, where their expertise allows them to spot and correct AI-generated errors automatically without feeling the need for formal verification. In contrast, those working with new or unfamiliar topics may engage in more deliberate fact-checking to compensate for their knowledge gaps. Furthermore, novice users are also more susceptible to AI misinformation, as they lack the background knowledge to recognize inconsistencies (Van Der Linden, 2022). Gen AI output can appear “authoritative” even when they hallucinated (Mai et al., 2024), as a result, those working with new or complex information may engage in more explicit fact-checking, while those familiar with the topic may rely on their own expertise. Understanding that not all AI users approach verification the same way, and why these differences occur allow teacher training programs to design AI literacy programs to address these different user needs. As experienced users may need less emphasis on verification skills but more focus on AI efficiency, and conversely, novice users might need stronger training in evaluative judgement (Tai et al., 2018) and AI literacy to avoid AI misinformation traps.

Our results reveal a gap in participants’ engagement with prompt refinement. Although prompting difficulties were the second most common challenge, few participants actively refined their prompts. This aligns with recent research on AI prompting, which identifies key challenges in formulating effective prompts, evaluating AI outputs, and integrating AI into tasks (Tankelevitch et al., 2024). Their metacognitive framework highlights two essential strategies for effective prompting: Prompt Formulation (defining task objectives and breaking them into sub-tasks) and Prompt

Iteration (revising prompts based on AI responses). The lack of prompt refinement suggests that pre-service teachers are not fully leveraging GenAI's potential, relying more on reactive adjustments than proactive prompt optimization. To address this, structured training in prompt engineering and metacognitive strategies is essential for enhancing GenAI's pedagogical use in education.

5.4 Feasibility of the Gen AI Readiness Scale

We also examined the feasibility of the GenAI Readiness Scale in this pilot study. We aimed to provide an initial assessment of these aspects among Finnish pre-service teachers. While most variables demonstrated acceptable reliability, some constructs - such as Anxiety and Perceived Accuracy - exhibited only moderate internal consistency. Given that these constructs were developed to capture the unique characteristics of GenAI tools based on emerging literature, further refinement is needed. Moreover, due to the small sample size, the scale's underlying structure could not be statistically validated through factor analysis. To enhance robustness and validity, future research should incorporate larger and more diverse samples and refine scale constructs and item statements as needed to improve reliability and measurement accuracy.

Limitations and conclusions

Our study has several limitations. First, its exploratory nature limits the generalizability of the findings. While offering initial insights into pre-service teachers' GenAI readiness in Finland, the results do not represent broader populations or diverse contexts. Second, the study captures a single moment in time, before systematic AI training programs were widely available. As GenAI evolves rapidly, longitudinal studies are needed to track changes in pre-service teachers' perceptions and behaviours. Finally, future research should explore how targeted AI literacy training shapes teachers' ability to integrate AI effectively.

This pilot study explored Finnish pre-service teachers' readiness, experiences, and behavioral intentions related to Gen AI, while also examining the feasibility of the GenAI Readiness Scale. The findings indicate varying levels of GenAI adoption, with a notable portion of participants having little or no prior use, while others engage with GenAI tools more regularly. Despite concerns about accuracy, frequent users prioritize usability, efficiency, and creative support, particularly for ideation and content creation. However, more advanced uses such as personalized learning and self-regulation support remain underutilized, which may reflect limited awareness, lack of experience, or appropriate caution given the emerging nature and uncertainties surrounding GenAI's educational applications. The study highlights the need for structured AI literacy training in teacher education, emphasizing not only skills in prompt engineering and evaluative judgment but also a thorough understanding of the ethical considerations and potential risks associated with GenAI integration. Future research should continue to explore how AI literacy development influences educators' adoption of GenAI tools, as well as the long-term impacts on teaching practices and the ethical use of AI in educational settings.

Research ethics

Author contributions

P.B.: conceptualization, methodology, validation, funding acquisition, writing - original draft preparation, writing - review and editing
T.K.: formal analysis, investigation, writing - review and editing
S.K.: data curation, investigation, writing - review and editing.

S.K.[2]: project administration, writing - review and editing.

S.P-H.: data curation, writing - review and editing.

M.V.: conceptualization, methodology, validation, writing - review and editing

All authors have read and agreed to the published version of the manuscript.

Artificial intelligence

The authors use ChatGPT for language checking purpose only.

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Institutional review board statement

This research followed the research ethical guidelines recommended by The Finnish National Board on Research Integrity TENK: https://tenk.fi/en and the Ethical Guidelines by the University of Turku, Finland.

Informed consent statement

Informed consent was obtained from all research participants.

Data availability statement

Data is not made publicly available due to privacy and ethical restrictions. Those who interested in the data can contact the first author for more information.

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Conflicts of interest

The authors declare no conflicts of interest.

Appendix A

Gen AI Readiness Scale Items (in English)

No	Items	Constructs	References
01	Using Generative AI enables tasks to be completed more quickly.	**Perceived Usefulness**	(Davis, 1989; Casey et al., 2021)
02	I believe that Generative AI technologies like ChatGPT can provide me with unique insights and perspectives that I would not have come up with on my own.		
03	Using Generative AI increases my productivity.		
04	I think that Generative AI technologies like ChatGPT can offer me personalized and immediate feedback and suggestions for my tasks.		
05	I plan to incorporate Generative AI technologies, such as ChatGPT, into my teaching practice and learning in the future.	**Behavioral Intention**	(Davis, 1989; Ayanwale et al., 2022)
06	I intend to keep myself up to date with the latest applications of Generative AI in the future.		
07	I am motivated to use Generative AI tools to develop learning materials for my students.		
08	Learning about Generative AI benefits my future teaching career.		
09	I see a strong connection between Generative AI technology and my future teaching practices.	**Relevance of Gen AI**	(Venkatesh & Davis, 2000; Ayanwale et al., 2022)
10	I can see a clear relevance of Generative AI knowledge to my personal life.		
11	I'm unsure about the practical relevance of Generative AI in my day-to-day teaching activities. (*reserved items*)		
12	I trust the accuracy and fairness of content generated by Generative AI tools.	**Perceived Accuracy of Gen AI**	(Venkatesh & Davis, 2000)
13	I have concerns about the potential biases in content generated by Generative AI tools. (*reserved items*)		
14	I am unsure about the consistency and reliability of content generated by Generative AI tools for educational purposes. (*reserved items*)		
15	I intend to verify the accuracy and reliability of content generated by Generative AI tools before		

	using it. (*reserved items*)		
16	When I reflect on the capabilities of Generative AI, I think about how difficult my future will be.	**Gen AI Anxiety**	(Venkatesh & Davis, 2000; Ayanwale et al., 2022; Li & Huang, 2020)
17	I feel anxious about keeping up with the rapid advancements in Generative AI technology.		
18	I feel uncomfortable and uneasy when I think about Generative AI.		
19	I am confident that I can introduce the most complex materials on Generative AI in class.	**Confidence in Using Gen AI**	(Venkatesh & Bala, 2008; Ayanwale et al., 2022; Tondeur et al., 2017)
20	I believe that I will succeed in clarifying Generative AI for students if I try hard enough		
21	I am confident that I can support students' learning of Generative AI in my lessons.		
22	I am confident that I can teach the fundamental principles of Generative AI in my lessons.		
23	I feel prepared to address the potential risks of using Generative AI tools, such as bias, misinformation, or hallucinations.	**Gen AI Readiness**	(Parasuraman & Colby, 2015; Ayanwale et al., 2022)
24	I have the up to date and relevant knowledge for using Generative AI.		
25	I have access to relevant and up to date content to learn about Generative AI in my program.		
26	I have the appropriate software for using Generative AI.		

Participants' Gen AI Experiences, Challenges and Coping Strategies Coding Book

Theme /code	Description / Definition
***Dimension*: Context** (Tasks are categorized based on their broader usage context)	
Learning-related	Tasks where participants explicitly mentioned to support their learning, such as writing, research, or studying.
Teaching-related	Tasks where participants explicitly mentioned in teaching contexts, including lesson planning, brainstorming activities, or designing materials.
General	Tasks where participants did not explicitly mentioned contexts, or do not fall exclusively into learning or teaching but involve general productivity.
***Dimension*: Functional purpose** (Tasks are categorized by their functional purpose, ensuring each mention is assigned to a single best-fit category to avoid overlap).	
Ideation	Participants use Gen AI tools to generate new ideas, brainstorm different perspectives, or overcome creative blocks.
Summarization	Participants use Gen AI tools to condense or summarize information / texts into key points or summaries. This includes summarizing research papers, articles, personal notes or discussions.
Revision & Verification	Participants use Gen AI tools to refine existing work by improving clarity, coherence, and correctness (*revision*) or ensuring accuracy and validity of information, arguments, or calculations (*verification*).
Lesson Planning & Material Design	(Teaching-specific) Participants use Gen AI tools to develop instructional content, structure lesson plans, or design teaching materials.
Concept Exploration & Problem-Solving	Participants use Gen AI to break down complex ideas, generate step-by-step solutions, or explore alternative approaches to a problem. This includes explaining abstract concepts or providing structured solutions.

Self-Regulated Learning	Participants use Gen AI to guide, design or monitor their own learning process through goal setting, self-assessment, personalized study plans.
Participants' experiences with Gen AI	
Positive experiences: Participants' perceptions of beneficial experiences with Gen AI	
Perceived Usefulness	Participants evaluated their experiences based on GenAI's ability to provide meaningful, high-quality contributions to tasks, including: generating new perspectives, enhancing understanding, or improving quality. The focus is on the *value* and *effectiveness* of Gen AI's output, rather than its convenience.
Usability & Productivity	Participants evaluated their Gen AI's experiences based on GenAI's ability to make tasks faster, easier, or more convenient: summarizing information, retrieving content, automating processes. This focuses on *efficiency* and *ease of use*.
Negative experiences: Negative experiences refer to participants' direct frustrations or dissatisfaction with Gen AI's performance in completing tasks	
Lack of Helpfulness	Participants found AI unhelpful when it failed to provide relevant, clear, or useful responses, requiring excessive clarification or effort to get meaningful results, including AI misunderstanding queries, giving irrelevant answers, or requiring too much back-and-forth interaction to be useful.
Concerns: Concerns refer to participants' apprehensions about potential risks and limitations associated with Gen AI. These concerns extend beyond immediate usability (i.e. lack of usefulness) and focus on trust, accuracy, ethics, misuse, AI awareness, and overreliance. Participants expressed caution about AI's reliability, its impact on academic integrity, etc.	
Trust and Accuracy	Concerns about the reliability and correctness of Gen AI-generated content, issues such as factual errors, miscalculations, inconsistencies, or unnecessary lengthy responses.
Ethical Concerns	Concerns about ethical implications of Gen AI use, regarding plagiarism, copyright violations, and the broader societal impact of AI-generated content.
AI Misuse and Wrongful Use	Concerns about academic integrity, institutional policies, or ethical guidelines. For example: Gen AI is used to complete assignments dishonestly or assist in academic dishonesty.
AI Awareness	Participants demonstrated an understanding of Gen AI's fundamental limitations, such as its biases, repetitive patterns, and lack of true intelligence. This category includes concerns about understanding / raising critical awareness of Gen AI's capabilities and the need for users to develop AI's awareness and AI literacy.
Overreliance in AI	Concerns that users may become too dependent on Gen AI tools, potentially weakening their critical thinking, problem-solving skills, etc. This category focuses on the risk of AI replacing independent learning rather than supporting it.
Challenges: The difficulties participants faced while using Gen AI tools.	
AI-generated Outputs	Problems with the quality, relevance, or accuracy of AI-generated responses: incorrect information, vague or repetitive responses, lack of depth, verbosity, or biased outputs.
Prompt Challenges	Struggles with crafting effective prompts to obtain useful responses. Issues included unclear responses due to vague prompts, difficulty refining questions, or needing multiple adjustments to get desired answers.
Competence	Challenges about the competence (or lack thereof) of Gen AI.
Solutions & Behavioral Intentions: This theme captures the strategies participants used to manage AI-related difficulties or their future approaches to using Gen AI.	

Modifications of Outputs	Participants reported to have manually edited, refined, or restructured AI-generated content to improve clarity, coherence, or accuracy. This includes rewriting text, reorganizing ideas, and removing unnecessary information.
External Verification & Critical Evaluation	Participants reported to have cross-checked AI-generated information using other external sources (e.g., books, academic papers, credible websites), or critically evaluated AI's output before accepting it (e.g. using their evaluative judgement).
Prompt Refinement	Participants reported to have adjusted, rephrased, or made prompts more specific to get better AI responses. This includes trial-and-error prompting, adding more context, or experimenting with different wording or in different languages.
AI for Specific Tasks	Participants reported to only use Gen AI tools for certain, specific tasks where it was most effective
Future Intentions	Planned adjustments in how they would use AI in the future.

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