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Generative AI Highlights the Contrast between Students' Dualistic Epistemic Practices and Teacher Education Learning Objectives

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Abstract: This study examines student teachers' capabilities when adopting a generative AI system as a new cognitive tool. In our pedagogical intervention, students used ChatGPT 3.5 to support a small research task. Consistent with decades of research on higher education students' epistemic positions, most students approached the knowledge-building task (and, respectively, ChatGPT) with dualistic epistemic practices. Notably, ChatGPT's polished interface invites naïve dualistic interpretations. However, teacher education learning objectives and effective knowledge-building with generative AI tools require more sophisticated epistemic stances: understanding knowledge as contingent and context-bound and knowledge-building as an activity that requires validation. This suggests that the central challenge for teacher education is not generative AI per se but supporting students' epistemic development so that they can use such tools responsibly.

Keywords: cognitive tool, epistemic position, epistemological belief, generative AI; hybrid intelligence; Perry scheme, teacher education

Introduction

The boom in generative artificial intelligence (GenAI) has placed serious pressure on higher education (HE) to reassess its established pedagogical practices (McDonald et al., 2024; Moorhouse et al., 2023). Institutional responses have varied widely. Some countries and institutions have imposed strict restrictions or blanket bans on the use of GenAI (UNESCO, 2023), while some have discouraged its use or instituted careful, cautionary guidelines for its adoption (McDonald et al., 2024). In contrast, after a brief initial negative reaction, many Finnish universities were among the early adopters of GenAI tools as an educational opportunity.

However, the adoption of GenAI in education is a case in which the solution is externally provided, and where educators look for problems it might solve. Nevertheless,

productive pedagogical use cases are emerging for a wide range of educational domains. For example, large language models (LLMs) can be used in programming education to help novice programmers interpret errors in their programs (Leinonen et al., 2023), and text-to-image generative models provide new tools for ideation and visual exploration in craft and design education (Vartiainen & Tedre, 2023). Importantly, however, some profound differences exist between GenAI and the digital cognitive tools traditionally used in teaching and learning. Digital cognitive tools (such as spreadsheets, databases, and educational software) are common extensions of learners' cognition, frequently used during knowledge construction activities. These kinds of tools amplify or scaffold human problem-solving and extend the range of problems to be solved, without replacing core cognitive work (Kim & Reeves, 2007). Like a pen or a calculator, their limited capability keeps the bulk of the cognitive work within the learner.

GenAI tools challenge the familiar relationship with tools (Vartiainen & Tedre, 2024). Their epistemic opacity, combined with intuitive user interfaces, could tempt learners to unwarily offload not just routine, familiar tasks, but substantial portions of their cognitive labor onto GenAI, thus undermining knowledge construction. GenAI tools designed to minimize users' cognitive processing per certain output might not be well suited for educational knowledge work, in which the aim is often to challenge learners to think and maximize their cognitive work (Vartiainen & Tedre, 2024). The combination of sycophancy (Malmqvist, 2025) and authoritativeness (Metzger et al., 2024) of language model outputs, for example, risks unintended cognitive offloading in learning. How to leverage the affordances of GenAI tools in pedagogical applications thus presents new challenges for educators.

Among the HE fields, teacher education (TE) represents a special case. After graduation, the newly graduated teachers should not only be able to *use* GenAI tools independently, but also integrate the use of GenAI tools in a pedagogically suitable manner, targeting their pupils' learning needs within learning environments available in future societal situations. Considering this, we designed a pedagogical intervention that positioned GenAI as a transformative cognitive tool. Together with our students, we aimed to explore the possibilities and constraints of rapidly developing GenAI technology. Thus, *this descriptive study aimed to deepen our understanding of student teachers' capabilities when adopting novel GenAI-based cognitive tools*—in this case, ChatGPT 3.5. We begin by outlining recent changes in the GenAI landscape and GenAI-related ethical and pedagogic concerns. Then, we summarize the learning objectives of Finnish TE and contrast those objectives with a model of HE students' epistemological beliefs.

Developments in the GenAI Landscape

While natural language generation is a decades-old research topic in computer science (Nilsson, 2009), the technology gained significant public attention with the launch of OpenAI's ChatGPT, which presented a chat-like interface to an LLM trained on a massive text corpus and fine-tuned with human conversational data (Shafik, 2024). The 2020s have since seen a number of breakthroughs in the GenAI field, with text-to-image generative models, text-to-music generative models, and LLMs that are widely featured and discussed in the mainstream media. The latest iterations of those systems fall under the larger category of foundation models—large-scale AI systems trained on massive amounts of diverse data, which enables them to carry out a broad range of tasks and even adapt to tasks for which their

training data contain no examples (Bommasani et al., 2021). Contemporary GenAI systems rely on foundation models to create new content in multiple modalities, such as 3D assets, videos, music, soundscapes, images, virtual environments (Leong et al., 2025), and, most relevant for this study, text.

Since the late 2022 launch of ChatGPT, the most visible GenAI progress for general audiences has come not just from improvements in foundation models themselves, but also from discipline-specific applications (Bommasani et al., 2021). Fields of application span natural language processing and text generation, healthcare, computer vision, the creative industries, and search engines augmented with LLMs (Zhang et al., 2025).

In the field of education, multiple views are held ranging from moral panic to hype. On the techno-enthusiastic side, reviews and meta-reviews anticipate that GenAI applications can provide students with 24/7 engagement and interactivity, personalized feedback and learning paths, as well as the automation of repetitive, routine tasks (e.g., Mittal et al., 2025; Noroozi et al., 2024; Wang et al., 2024). Language learning structured writing and data analysis are frequently mentioned areas of promise. A recent systematic review of GenAI tools in HE (Qian, 2025) found that ChatGPT dominates use despite the availability of numerous other tools. Furthermore, traditional pedagogical approaches have continued to prevail: GenAI tools were more often used to automate existing tasks than to rethink learning tasks and objectives in light of the interactive and collaborative affordances of GenAI (Qian, 2025).

This slow adoption of pedagogical practices and priorities is also reflected in the four educational roles for GenAI tools and systems identified by Wang et al.'s systematic review (2024): intelligent tutor, intelligent tutee, intelligent learning tool/partner, and domain expert. As an "intelligent tutor," a language model is used to summarize texts or demonstrate tasks. In the "intelligent tutee" role, it is used to automate encouraging learners to provide feedback, for instance, for further iterations of generated content. A language model as a "learning partner" refers to using the model to help organize one's thoughts or provide illustrations based on textual prompts, which frees learners' cognitive resources for other activities. As a "domain expert," language models can be used to generate "advice" on special topics (Wang et al., 2024). Notably, three of these four roles position students primarily in their traditional role of knowledge recipient, and the language model in the role of the knowledge authority (or, in the case of text-to-image generators, of the visualization authority). Such positioning mirrors traditional teacher-centered dynamics, leaving little room for student agency, inquiry, or epistemic ownership. Whether these roles facilitate learning or undermine it is an empirical question, with results suggesting the latter is likelier the case (Kosmyna et al., 2025).

Some techno-enthusiastic claims have been countered with empirical results on the use of language models in education that show negative consequences of AI dependency, such as reduced critical and independent thinking, lower creativity (Zhang et al., 2024), underperformance at the neural, linguistic, and behavioral levels (Kosmyna et al., 2025), fewer flow experiences, lower self-efficacy, and decreased learning achievement (Yang et al., 2025). These kinds of results are especially detrimental for TE. Notably, research on GenAI-related pedagogical practices and their consequences, especially on interventions supporting students' agency, is limited (Yang & Markauskaite, 2025).

Developments in GenAI have complicated the longstanding questions about how AI is transforming epistemic practices across the sciences, work life, and everyday life, redefining how we generate, validate, and utilize knowledge about the world. In the realm of science, GenAI-based systems continue the decades-long trajectory in which computers have

fundamentally altered epistemic practices across disciplines (Denning & Tedre, 2019). Beyond the sciences, GenAI systems are also becoming part of the evolving automation of knowledge work due to their adaptability in performing a wide variety of tasks associated with knowledge creation (Agüera & Norvig, 2023; Bommasani et al., 2021; Brynjolfsson & McAfee, 2014).

Ethical Concerns regarding GenAI

Like many other digital technologies, GenAI tools are protean, opaque, and unstable, but also revolutionary, as they are generative and social (Mishra et al., 2023). Current text-to-image generative models, such as DALL-E 3, Firefly, or Nano Banana, can provide several options per prompt, thus allowing users to compare alternatives. In contrast, text-generation models, such as ChatGPT, typically return a single answer at a time. This one-answer convention effectively conceals the need for user discretion. In comparison, search engines, such as Google Search, present a list of results, inviting the user to compare, evaluate, and choose. More importantly, search results display the source websites, enabling the evaluation of the trustworthiness of the information (Lewandowski, 2008). A single, authoritative response suggests a high truth value and obscures the stochastic nature of LLM outputs. Rather than incontestable truths, these outputs reflect the most probable construct of word sequences derived from massive, largely opaque text corpora, which makes it difficult for users to assess reliability or bias (Wang et al., 2025).

GenAI-based tools and services are transforming the context of human learning, action, and epistemic practices. AI-enabled tools and technologies increasingly mediate people's daily actions and decision-making within a new media ecology characterized by ubiquitous data collection, profiling, and recommendation systems that tirelessly curate, target, and personalize people's information feeds (Valtonen et al., 2019). This influences how people consume and construct knowledge, and ultimately how they form epistemic beliefs and conceptions of truth (Coeckelbergh, 2023). This complexity is further intensified by the ethical, legal, societal, and environmental implications of GenAI (Bommasani et al., 2021; Shelby et al., 2023), leading to complex moral questions ranging from copyright and privacy concerns to sustainability issues, power relationships, and unethical usage, such as manipulation through mis- and disinformation (Vartiainen et al., 2024). As Hintz et al. (2019) noted, understanding the mechanisms, power, limitations, and ethical concerns of AI is crucial for active citizenship, but also for the prosperity of democratic societies—and for the education of future generations whose lives are increasingly likely to involve AI-driven technology.

At the same time, professionals are increasingly compelled to integrate AI tools into their specialized, context-specific practices (e.g., Lim & Nicolaides, 2024). This has given rise to new expectations, and debates have emerged regarding the nature of the professional knowledge and skills needed in the age of GenAI tools. Consequently, several HE institutions have issued policy papers (McDonald et al., 2024). As a cognitive tool, GenAI systems have affordances and constraints specific to the HE context—specific to each disciplinary tradition, learning task type, learning environment, and learner—but also to the particular GenAI applications. Recent TE-related discussions can be found, for instance, in Dilek et al.'s (2025) and Searson et al.'s (2025) work. Locally, emerging discussions on the AI Assessment Scale (a scale used to determine which AI use should be encouraged for a given learning task; Perkins et al., 2024) should emphasize *the nature of the epistemic practices*

that students allocate to AI. Fundamental questions for education, particularly for TE, include how students’ epistemic agency should be cultivated in the age of GenAI and what AI competencies will be valuable for teachers.

TE Learning Objectives: The Finnish Perspective

The Finnish educational system considers teachers as autonomous professionals. For instance, schools and teachers are responsible for local curricula and for choosing teaching methods and materials (Niemi et al., 2018). To ensure the required competence, teacher qualifications involve a master’s-level degree (300 European Credit Units), with an emphasis on a research orientation (Toom & al., 2010). Objectives for future teachers, set by the Finnish Ministry of Education and Culture (FMEC), involve three large thematic areas and sixteen competences (FMEC, 2016). From these, twenty-six objectives for TE have been derived (Jyrhämä, 2021), covering domains, such as the capability to adapt science-based pedagogic knowledge ethically and reflectively, foreseeing and leading change, as well as deploying innovations and digital tools (Figure 1). Thus, adopting and adapting novel cognitive tools is not a new expectation for Finnish teachers and TE.

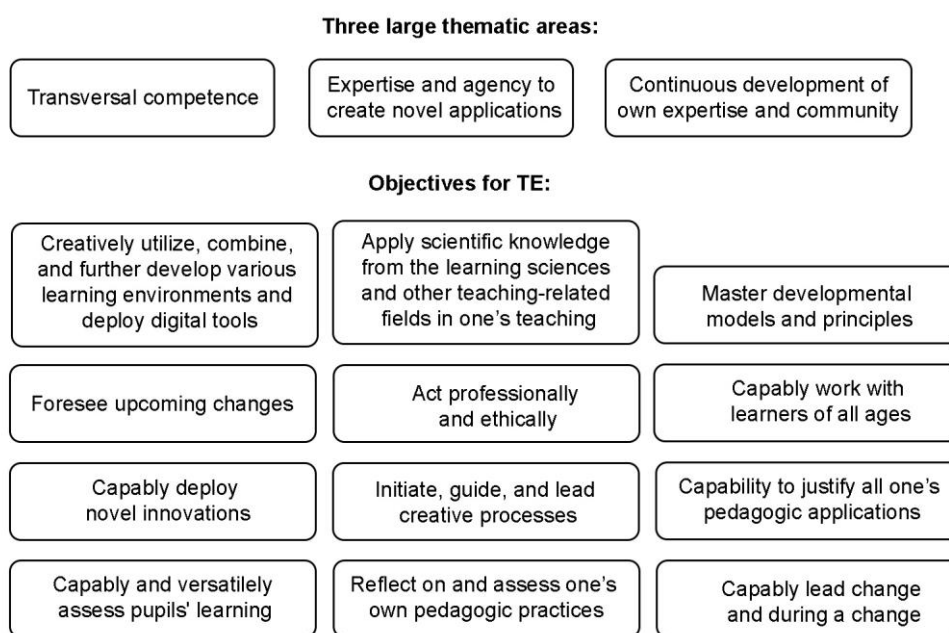


Figure 1: Examples of objectives for Finnish TE (adapted from FMEC, 2016, and Jyrhämä, 2021)

In practice, Finnish TE programs involve courses on the theoretical foundations of teaching, learning, and subject didactics, practice periods, and studies in pedagogic research methods, as well as bachelor’s and master’s theses (Jyrhämä, 2021). Research activities enhance critical and creative thinking capabilities (Toom et al., 2010). Moreover, multiple transferable skills related to knowledge-building are developed through having a research orientation (Figure 2). Generally, research skills equip student teachers so that they can become pedagogically thinking, reflective, and inquiry-oriented, which is the ultimate aim of research-based TE (Toom et al., 2010).

Moreover, contemporary TE should futureproof students with adaptive skills and attitudes toward digital cognitive tools, such as GenAI tools. A decade ago, Finnish TE recognized the need to replace the idea of mastering *specific information and communication technologies* (ICTs) with the need to master *rapid developments* in the ICT field as a key challenge (Tirri, 2014). GenAI, as a rapidly changing, opaque technology, takes this challenge to a whole new level. Teachers’ use of technology is influenced by their knowledge bases on technology (Mishra et al., 2023) and their personal–professional use and beliefs (Almerich et al., 2024), especially beliefs about the nature of knowledge and learning (Kim et al., 2013). Thus, *GenAI pedagogy in TE should involve not only technological but also epistemological aspects*.

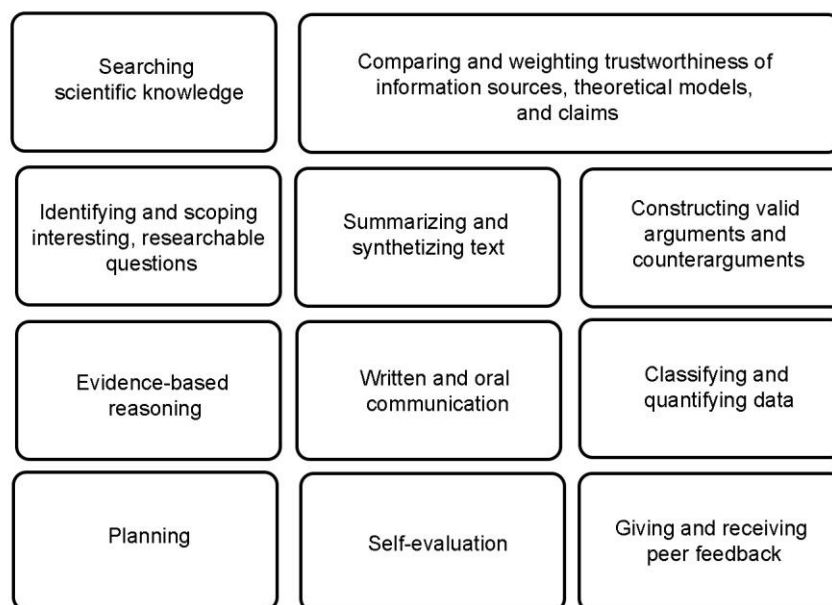


Figure 2: Examples of transferable skills that can be acquired through learning research activities and knowledge-building

HE Students’ Epistemological Beliefs

The above-mentioned challenges to TE are not independent of students’ knowledge, skills, and agency. As Hofer and Pintrich’s (1997) review on epistemological theories shows, HE students have varied epistemological beliefs (i.e., beliefs about the nature of knowledge and knowing), which can change over time, and can vary from discipline to discipline. Epistemological beliefs are activated when learners engage in learning and knowing (Hofer, 2002), and they influence study strategies and learning outcomes (e.g., Muis, 2004; Schommer-Aikins, 2002). Understanding students’ epistemological beliefs can enhance the effectiveness of teaching (Hofer, 2002) and thus facilitate the development of a purposeful GenAI pedagogy.

A range of empirical theories (and their critics) have addressed individuals’ conceptions of knowledge and knowing as manifold (see Hyytiäinen et al., 2020 for a recent review). The Perry scheme (1970/1998) was the first study on HE students’ epistemological

beliefs and their development. Although Perry's study began in the 1950s, his seminal scheme has remained influential in research for more than five decades (Richardson, 2013). The Perry scheme describes four categories and nine positions (P1–P9) for HE students' epistemological beliefs. Our adaptation of the Perry scheme, based on Perry (1970/1998) and Gainsburg (2015), is shown in Figure 3.

Notably, prior research shows that a clear majority of HE students occupy positions below P5 (e.g., Carmel-Gilfilen & Portillo, 2011; Gainsburg, 2015; Perry 1970/1998; Smith, 1984) within the categories of dualism and multiplicity. In contrast, TE objectives aim for students to reach contextual relativism (P5–P6). Furthermore, the above-mentioned expectations placed on Finnish teachers mean that student teachers should develop a teacher professional identity and practical theory suitable for the education profession (Toom et al., 2010). This requires commitment within relativism (P7 and above), or at least P6, entailing the anticipation of commitments. Reaching the TE objectives—and the respective Perry Positions—is a significant challenge for educators. The transformation to P5 is the most significant transformation within the Perry scheme (Perry 1970/1998), but both of these transitions reflect one's professional growth: the process of becoming a member of an expert community (Perry, 1970/1998). This process is elemental for becoming a university-educated teacher.

Research Questions

From these starting points, we formulated two research questions (RQs):

- RQ1 What types of ChatGPT use can be identified in students' reports?
- RQ2 What GenAI-related concerns did students raise in their reports?

In the following section, we describe our study setting and pedagogic intervention, methods, and the results of our thematic analysis. Based on our findings, we discuss TE learning objectives and possible actions to strengthen students' GenAI-related competence in deploying hybrid intelligence.

Category/ positions	Dualism Positions P1 P2	Multiplicity Positions P3 P4	Contextual Relativism Positions P5 P6	Commitment within Relativism Positions P7 P8 P9
Knowledge	Right or wrong Truth can be found by using proper methods	Right, wrong, not yet known "Unknown" means the right method to solve the question has not been found	Multiple answers Quality of answers depends on context	There may not be a correct answer Acquisition of knowledge as an ongoing activity
Individual's relation to knowledge and knowledge production/ problem solving	One receives knowledge: Authority has Absolute Truth and should convey the Truth to the learner. P1: Only one, unquestioned Authority exists. P2: Several Authorities, but only one has the Truth, others are wrong. Problem solving is about making the right moves, strictly following a recipe.	Dualism begins to dissipate; one recognizes diversity and uncertainty. P3: The truth is knowable, eventually the right answer to any problem can be found. P4: Some problems are unsolvable: "We'll never know for sure." Then, all views are equally valid, everyone has a right to one's own opinion. One solves problems with method that best makes sense for oneself.	One recognizes that knowledge is context-bound and constructed by oneself. One needs to evaluate answers. P5: Generally, multitude of correct answers is accepted, but all knowledge and authority are acknowledged as contextual. P6: Knowledge is relative, contingent, contextual. One needs to choose one's own commitments, as relative quality of ideas can be judged on the basis of logic, other knowledge, and experience.	One has agency to judge among ideas/views. The agency is grounded on personally meaningful commitments to values, career, politics, or personal relationships. P7: One makes an initial commitment to a stance. P8: One explores commitment and its implications. P9: Developing and refining of commitments.

Figure 3: Main categories and positions of the Perry scheme (adapted from Gainsburg, 2015; Perry, 1970/1998)

Methods and Materials

As data for this qualitative descriptive study, we collected all of the materials produced from the pedagogic intervention. The data were analyzed using thematic analysis, as it provides flexibility in choosing themes according to their importance in relation to the RQs instead of occurrence frequencies (Braun & Clarke, 2006). Thematic analysis is especially suitable when seeking an understanding of experiences, thoughts, or behaviors (Braun & Clarke, 2006). Thematic analysis approaches vary from realistic to constructionist, from inductive/data-driven to theory-driven, and from semantic to latent/interpretative (Braun & Clarke, 2006). Because the research topic at hand is currently under-researched, we chose an inductive and interpretative approach.

Research Design: Pedagogic Intervention in TE

The intervention context involves a bachelor's-level course aimed at strengthening students' research skills from the viewpoint of teachers' practical work. This second course on pedagogical research skills is compulsory for all TE students at the university in question. The coursework includes a report of small-scale pedagogical research involving the design of a survey instrument, conducted in pairs. To ensure motivation and pedagogical relevance, the students chose their own research topics.

Rapid changes in the GenAI landscape in 2023 encouraged us to introduce the basics of GenAI to students. We wanted to ensure our students gained the advantage of belonging to (if not as early adopters but at least as) the early majority cohort. After weighing the relevant ethical concerns, our GenAI choice was ChatGPT 3.5 due to its accessibility to students at the time. The introduction focused on the LLMs' fundamentals, the utilization of ChatGPT in research, and prompt design. LLMs were characterized as models of training data rather than models of reality, and ChatGPT was characterized as a word prediction system rather than as a search engine. The need to verify all ChatGPT output was repeatedly stressed, as were the ethical issues related to authorship, plagiarism, and referencing. ChatGPT was introduced as an intelligence augmentation tool supporting one's learning and reflection rather than as a tool replacing one's need for independent cognitive work. Students were asked to utilize ChatGPT in their coursework and report as clearly as they could the ways in which they used ChatGPT (e.g., by using different colors for parts provided by ChatGPT, parts representing students' own thinking, and parts including ChatGPT output modified by the students). The suggested applications of ChatGPT included searching for ideas, paraphrasing, outlining, summarizing, and proofreading.

Research Data and the Analysis Method

The primary research data included the students' coursework reports. Of all the course's learning groups, two were chosen for the intervention. All twenty-nine students belonging to these two groups gave their informed consent. Working in groups of two or three, students produced twelve reports. Our data-driven analysis followed the guidelines of Braun and Clarke (2006) for performing thematic analysis. Figure 4 describes the analytical activities, while the developed themes and codes for RQ1 are available in Figure 5 and, for RQ2, in Figure 6.

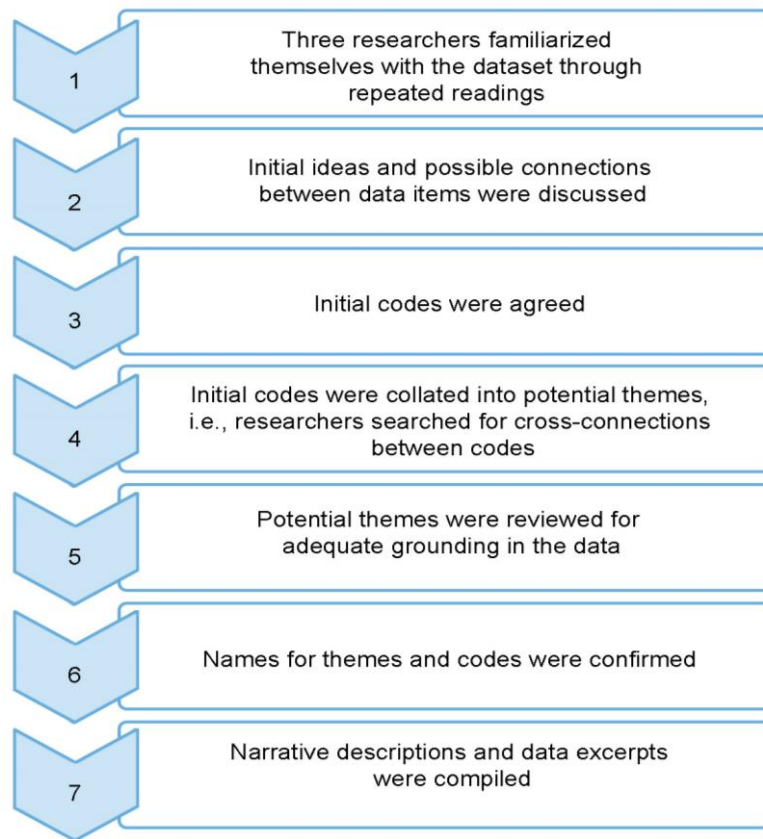


Figure 4: Collaboration by three researchers: Steps of the thematic analysis

The study followed the ethical principles issued by the Finnish Advisory Board on Research Integrity (FNBORI, 2023). The students' participation was completely voluntary, and they were informed that they had an unconditional right to withdraw at any time and without giving any reason.

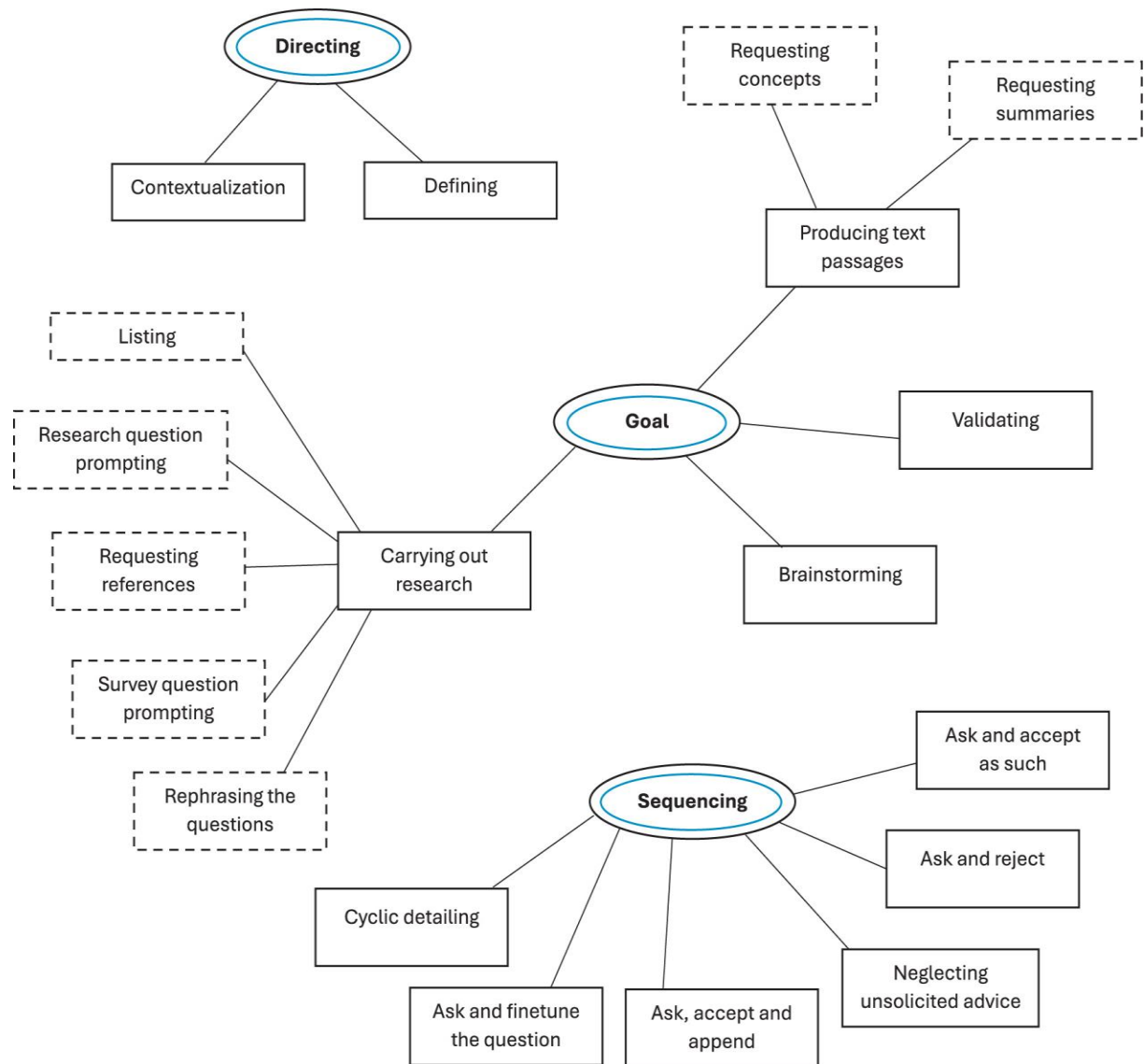


Figure 5: Themes and codes for RQ1: Types of ChatGPT use

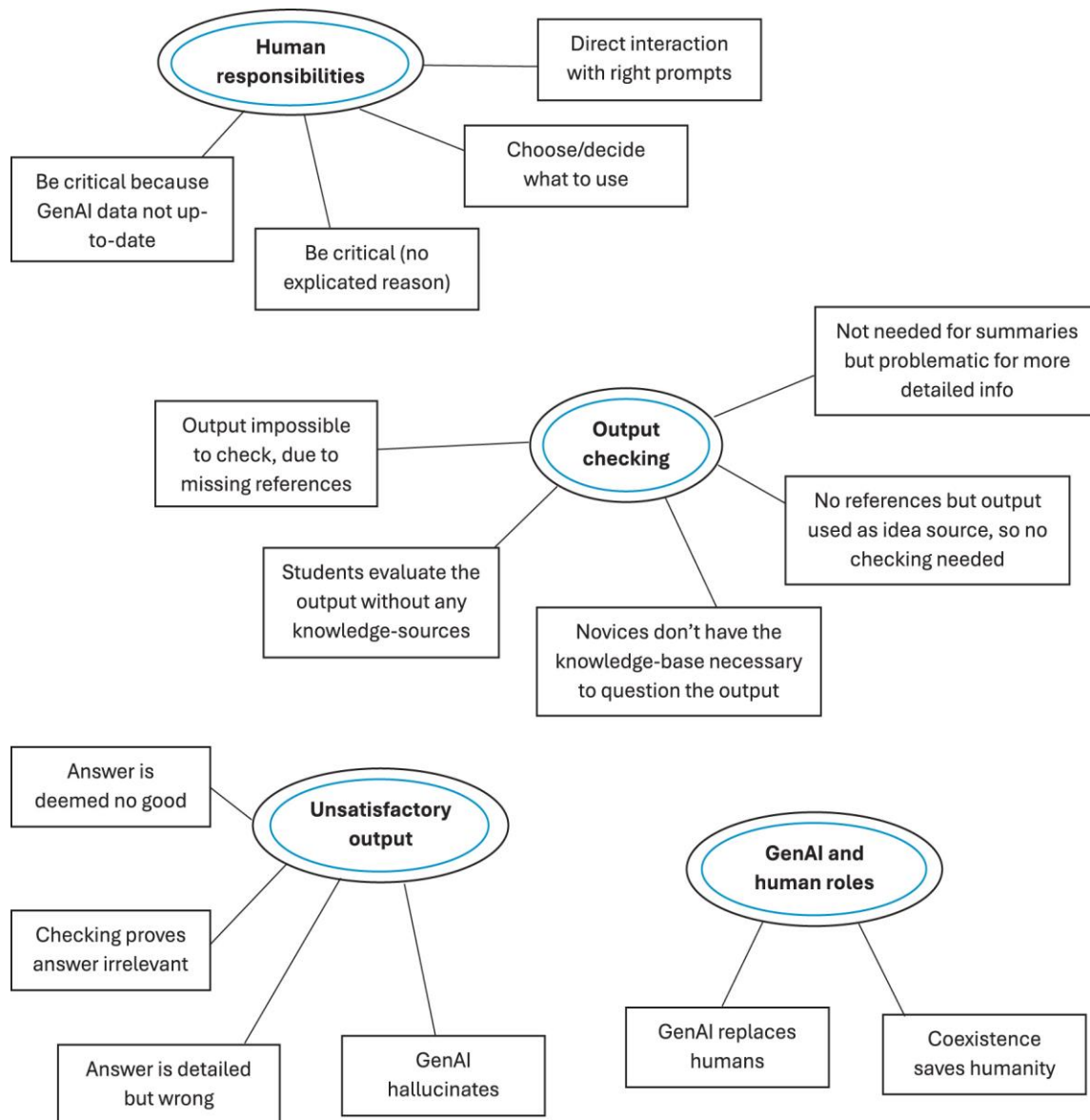


Figure 6: Themes and codes for RQ2: GenAI-related concerns raised by students

Results

In the following, a *request* refers to students’ prompts, a *response* refers to a ChatGPT answer to students’ requests, and an *action* refers to students’ reactions to responses. The themes, codes, and some illustrative data excerpts are accompanied by our findings. The numbers in parentheses indicate the source of the excerpt (report ID-citation ID).

RQ1: Types of ChatGPT Use

The types of ChatGPT use involved three different themes. Groups (1) directed ChatGPT with their prompts and (2) attempted to reach certain goals. These directions, ChatGPT responses, and the groups' further actions formed activity sequences (3).

Directing

“Directing,” which refers to instructing ChatGPT (i.e., prompting), was limited and minimalist. Two forms of directing were identified (Figure 7).



Figure 7: Codes for the theme “directing”

With contextualization, the students outlined a certain context, while defining provided a specific concept for GenAI. Typically, students did not reveal all the specifics, even when the request concerned a topic unique to the Finnish educational system: “What does multi-material crafts stand for in basic education?” (6-1). These students missed the central point of carefully formulating their initial request. This could indicate that ChatGPT was viewed as omniscient, that students held an epistemic belief in concepts as universal truths, or that students had forgotten their first-year course explaining the Finnish National Core Curriculum and of craft holding different meanings in different countries.

Goal

A “goal” refers to the targeted results of the interaction between students and ChatGPT (Figure 8).

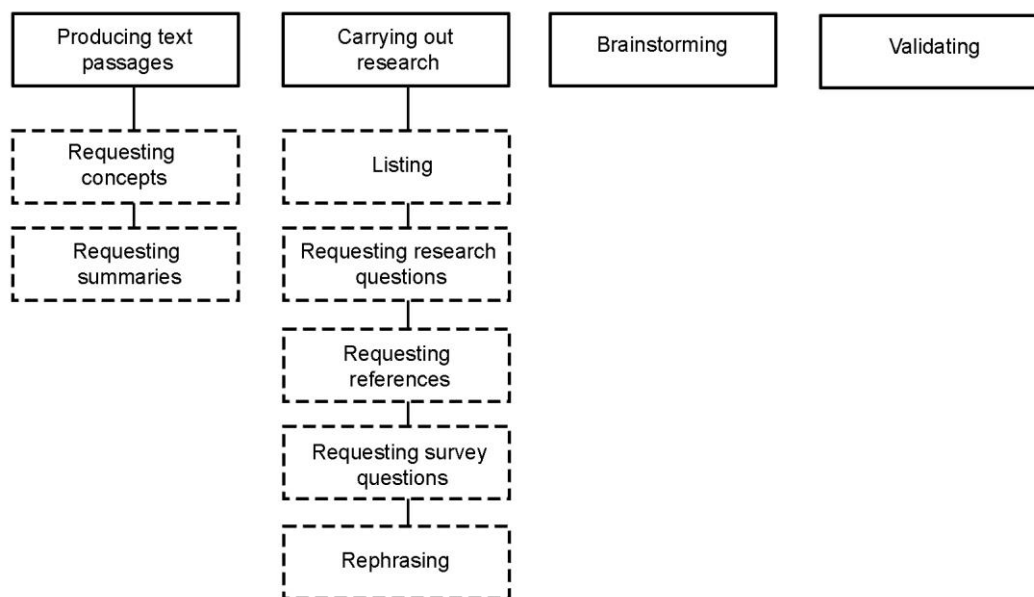


Figure 8: Codes and subcodes for the theme “goal”

The first code, “producing text passages,” includes the subcodes of “requesting concepts” and “requesting summaries” that reflect stereotypical ChatGPT use: “Tell me about creative thinking in education” (8-1). The second code, “carrying out research,” refers to students utilizing a straightforward strategy to request whatever they needed: a list of concepts related to a research topic (“listing”), research questions (“requesting research questions”), references (“requesting references”), survey questions (“requesting survey questions”), and “rephrasing.” These interactions were typically very brief, comprising one request and one reply. In contrast, the third code, “brainstorming,” refers to students experimenting with requests to broaden their perspectives. For this, the groups used different search terms, definitions, and references in their requests, and they examined ChatGPT responses critically to identify directions in which to proceed.

All three codes above reflect goals within ChatGPT’s capabilities, but the fourth code, “validating,” revealed two misconceptions. Students reported asking ChatGPT to comment on their research question: “We asked ChatGPT if this was a good research question, and it said ‘Yes, it is’” (8-2). The misconceptions concerned ChatGPT affordances and scientific research. Research questions are intimately connected with the research aims but also with the researcher’s position, reflecting the researcher’s values, objectives, and timely research topics (trends and biases). Rather than being right or wrong as such (reflecting P1–P2), they reflect commitments (P6–P9), over which ChatGPT has no authority to rule and no access to, unless explicitly included in the prompts.

Sequencing

“Sequencing” describes the activity sequences that students described in their reports (Figure 9).

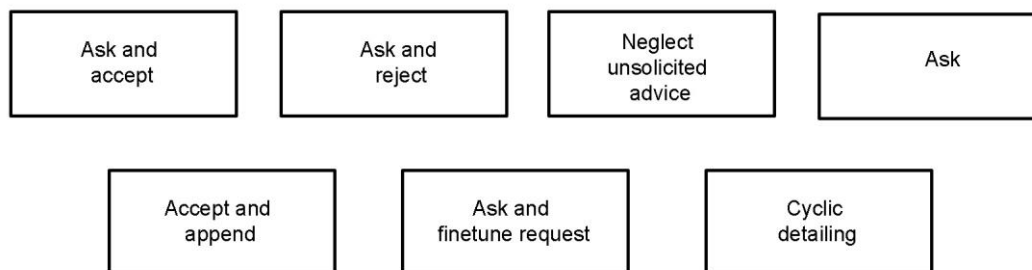


Figure 9: Codes and subcodes for the theme “sequencing”

A typical sequence entailed a ChatGPT response copied to the report (“ask and accept as such”). However, the shortest sequence was “ask and reject,” in which the response was not used at all and the interaction was discontinued. A related but special case involved “neglect unsolicited advice.” In a few cases, ChatGPT’s response included advice on how to proceed (e.g., search terms or databases), which students ignored. Simple but slightly longer sequences involved modifying ChatGPT’s response to the report (“ask, accept, and append”).

In contrast to the above three codes, the following two codes refer to students continuing to interact with ChatGPT after its first response. At times, students utilized ChatGPT’s response to advance prompting (“ask and finetune request”). However, the modifications were typically minor. In the following example, the students’ original request was, “What kinds of questions [should] I ask in the [trademark name] survey on the differences in the implementation of basic education crafts between different schools and its impact on the number of students in the elective subject of crafts?” One long question was divided into two questions, and the word order and wording were subtly changed: “And what kinds of [survey] questions for research on how the implementation of the craft subject in primary education differs between schools and how do those differences affect the number of students in elective craft subjects?” (4-1).

Two groups engaged in longer interactions. The “cyclic detailing” code refers to students continuing interactions after the first ChatGPT response by making detailed, clarifying requests: “I would like to understand why lower secondary school students choose [textile craft or technical work] as an elective course,” followed by “In particular, the social impact is interesting. Has there been any research on this?” and furthermore, “I was referring to the importance of social influence on the choice of [course]” (11-1). Prompting with dialogue-like continuity resulted in the effectual use of ChatGPT.

To summarize, both “finetuning the request” and “cyclic detailing” suggest that students understood that ChatGPT could refer back to previous interactions. However, this type of sequencing—treating ChatGPT as a cooperative partner—was scarce. Moreover, in the majority of cases, the groups adopted ChatGPT responses as such, without any criticism or validation based on independent sources. This could suggest likening ChatGPT to an encyclopedia or omniscient authority (P1–P2).

RQ2: GenAI-related Concerns that Students Raised in Their Reports

In general, this topic received very little attention, and three groups did not express any ChatGPT-related concerns. The identified themes contained “human responsibilities,” “response checking,” “unsatisfactory response,” and “GenAI and human roles.”

Human Responsibilities

One-third of the reports explicated “human responsibilities” (Figure 10).

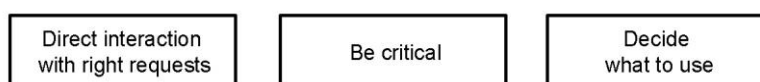


Figure 10: Codes related to the theme “human responsibilities”

“Direct interaction with the right requests” emphasized the value of meticulous prompting to get worthwhile answers: “ChatGPT was a good planning tool once the right attributes were added to the conversation” (12-1). Contrary to the RQ1 results (showing that typically very limited, if any, context was given to ChatGPT), this group had internalized the role of prompting and meticulous wording and their accountability in directing and re-directing the interaction rather than settling with whatever responses were given by ChatGPT.

“Be critical” involved two aspects: one reasoning that criticality was necessary because ChatGPT data were not up to date, and the other providing no reasoning whatsoever. The first case reveals only a partial understanding of GenAI operating principles, but the latter implies students parroted messages from their teacher and the mass media, thus suggesting dualistic Perry Positions (P1–P2).

“Decide what to use” was mentioned once: “ChatGPT has given us concepts for our frame of reference, but that didn’t cancel our need to ponder the concepts and decide what concepts we should use” (8-3). Thus, even though the RQ1 results suggest that most groups rarely considered the trustworthiness of ChatGPT responses, this group understood their accountability. As this group’s report provided no indications of cross-checking with other sources, we infer that they trusted their own knowledge, which reflects P4.

Response Checking

Only two reports explicitly stated the need to check ChatGPT responses. However, three others implied that this need existed; they were concerned about a lack of references. This caused various reactions, which were captured by the following codes (Figure 11).

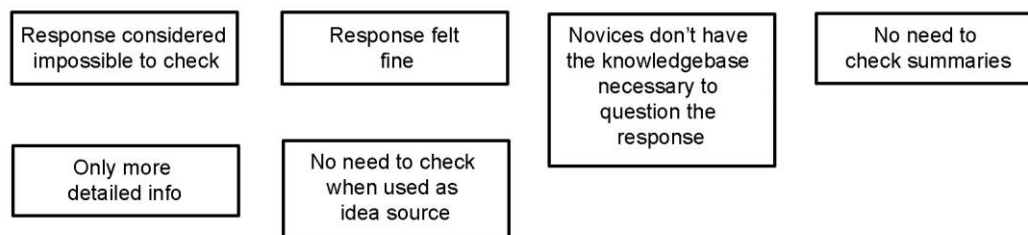


Figure 11: Codes related to the theme “response checking”

For the theme of “response considered impossible to check,” the group noted, “ChatGPT gave no sources for its answer, so we could not evaluate them” (7-3). This implies that the group felt helpless and that a lack of effortless means relieved them of the responsibility of cross-checking. On another occasion, the same group decided that they could rely on their own knowledge, as the following code “response felt fine” represents: “We asked for central concepts [...] and sources. We couldn’t check the sources, but the ideas were good, and we could proceed with them” (7-1). This also suggests Perry Position 4: The group considered that they had the necessary knowledge to validate ChatGPT’s response.

In contrast, as the code “novices do not have the knowledge base necessary to question the response” represents, another group claimed to be novices, thus renouncing the group’s agency and transferring the responsibility to validate the answer to readers of the report: “ChatGPT produces answers nicely, and in a novice student teacher’s eyes, it looks quite true” (5-2). This resembles Perry Positions 1–2.

Two different codes renouncing the need to cross-check appeared in the data: “no need to check summaries, only more detailed info” and “no need to check when used as an idea source.” The first case signals either blind trust in ChatGPT or a sloppy attitude. In the second case, the groups utilized ChatGPT as a way to develop their knowledge and thinking. This reflects Bereiter and Scardamalia’s (2003) “knowledge design mode” (pp. 55–56): When utilizing ChatGPT responses as springboards for ideation, the truth value is less meaningful than inspirational potential. Thus, the utilization of the response determines the significance of truthfulness, which suggests a Perry Position above P5.

Unsatisfactory Response

Typically, the groups’ expressions of discontentment were not targeted at any specific GenAI interaction. Three different cases in which groups were unsatisfied with GenAI answers included “hallucination,” “weak info,” and “poor info” (Figure 12).

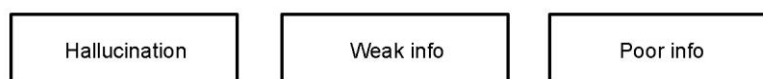


Figure 12: Codes related to the theme “unsatisfactory response”

The first two cases were related to ChatGPT-given source information, which the groups checked. For “hallucination,” the group found the source to be non-existent, and for “weak info,” only marginally relevant. These codes imply that groups understood the need to evaluate ChatGPT responses (Perry Positions 5–6: contextual relativism). However, for “poor info,” the group evaluated ChatGPT’s response as poor based on their own knowledge (P4).

GenAI and Human Roles

This theme is closely related to the first theme, “human responsibility.” One group reported two concerns: “GenAI replaces humans” and “human coexistence with GenAI” (Figure 13). As students did not provide a more detailed explanation of their concerns, these concerns could reflect wider AI-related discussions in the mass media, or they could indicate groups’ (beginning) understanding of value commitments (P6 and above).

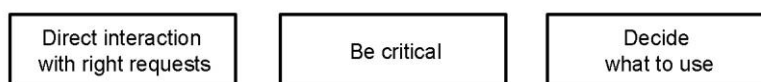


Figure 13: Codes related to the theme “human responsibility”

Discussion

Students were tasked to test ChatGPT’s capabilities, but with a critical attitude. The groups’ reported epistemic activities imply that the basics of LLMs’ affordances and constraints had not been captured (cf. Mishra et al., 2023). On the one hand, when ChatGPT’s answers pleased them, groups treated ChatGPT as an authoritative fact-finding machine—as a knowledge base rather than as a stochastic parrot producing seemingly coherent text without any responsibility for truthfulness (Bender et al., 2021). Groups dodged their responsibility for cross-checking by treating ChatGPT answers as valid enough as such or claiming themselves to be incapable of cross-checking. On the other hand, when the groups understood ChatGPT’s expertise on a given topic as dismal or unattractive, they discontinued their interaction with it.

Many groups tried to use ChatGPT for tasks outside its limitations of use. They also took over tasks (such as shortening the ChatGPT response) that ChatGPT could have done on their behalf. Most did not attempt to benefit from the conversational micro-context—that is, ChatGPT’s (limited) ability to refer to previous interactions. In effect, most sequences resembled unilateral activity (using a dumb machine) rather than interaction (i.e., mutual or reciprocal action). Rather than ideas, many requested answers to parts of the learning assignment, completely offloading epistemic work to ChatGPT.

Students’ reports exhibited several misconceptions related to the epistemic practices required for research. Some groups suggested missing source information as a major problem, which implies an understanding that a source equals a good enough argument and that no further validation is required. Some claimed that missing source information prevented them from cross-checking the answer, suggesting that they saw the validation of scientific knowledge as an activity used to check whether the named source contained the claim, after which no further action was required. No one described validation through

comparing several sources, the contextual validity of conflicting positions, or epistemic, ontic, or axiologic commitment.

We consider that these results reflect the groups' epistemic practices during knowledge-building together with ChatGPT. As a digital cognitive tool, ChatGPT represents a new type of tool that eludes some established theories on the role of tools and the locus of control in tool-mediated action (Vartiainen & Tedre, 2024). Effortless use through an interface mimicking human conversation, combined with total opacity, can create an illusion of control. ChatGPT's unassuming user interface (incorrectly) promises unrestricted access to a vast knowledge base. The interface suggests that truth is not only knowable, but that it is known. One only needs to ask the Authority: ChatGPT. *The user interface operates at the level of dualistic, naive Perry Positions (P1–P2), while in fact, knowledge-building with ChatGPT calls for continuous validation and operating from Perry Positions 6–9: anticipated or committed relativism.* A noticeable number of group reports reflected epistemological practices around Perry Positions 1–4. These results concur with earlier pre-ChatGPT results on the multiplicity of research (e.g., Carmel-Gilfilen & Portillo, 2011; Gainsburg, 2015; Perry, 1970/1988; Smith, 1984). Considering the above-discussed TE objectives reflecting Perry Positions 6–9, GenAI tools pose a challenge to students' epistemological and intellectual development.

Ease of use repositions the use of GenAI tools from the field of technological competence to the field of wider socio-cognitive competence. The above-mentioned learning objective for Finnish TE ("master rapid developments in the ICT field") is red hot. First, it is questionable whether one can *master* an opaque field that develops as rapidly as GenAI. Second, due to GenAI, TE's ICT mastery needs to be complemented with an understanding of epistemological theories, such as the Perry scheme. The adoption of GenAI tools is not merely a technological challenge, but an epistemological one. The Perry scheme suggests that *reaching TE objectives necessitates significant qualitative changes in students' approaches to their learning.* Traditional recommendations suggest challenging students to reflect on their domain-specific knowledge practices (e.g., Perry, 1970/1998; Richardson, 2013). Recommendations to accommodate GenAI in HE teaching suggest enhancing authenticity and requiring students to use GenAI at various stages during learning tasks (e.g., McDonald et al., 2024; Moorhouse et al., 2023). Taking the TE perspective, Yang and Markauskaite (2025) conducted a formative intervention to develop student teachers' transformative agency in relation to GenAI tools. During a formative intervention, students noticed that reaching good quality outcomes required that they used their existing knowledge about task-specific context and content and asked ChatGPT to finetune its output (Yang & Markauskaite, 2025). This exemplifies knowledge work at Perry Positions 6–9. However, the need to change epistemic practices concerns not only students and learning tasks, but also TE itself.

Limitations

This small-scale pedagogic intervention produced insights into students' epistemic practices and their understanding of GenAI principles. In the TE reality, the time given to students to complete this learning task was relatively short, and only a few lessons could be dedicated to instruction on LLMs and ChatGPT. In addition to epistemic beliefs, the results could reflect student motivation and well-being, as well as their capabilities in terms of self- and co-regulating their epistemic activities.

Utilizing the Perry scheme to anatomize students' group-level epistemic practices from a learning task is not the original aim of Perry's theory. While the Perry scheme fairly clearly describes the epistemological movement from dualism to relativism, the construction of knowledge beyond these positions is less well defined (Hofer & Pintrich, 1997). Gainsburg (2015) noted that distinguishing between multiplicity and contextual relativism was the most tentative aspect of his analysis, and ruling out certain levels was difficult. We concur. Our analysis did not aim to recognize personal or even group-level epistemic beliefs, but epistemic practices, which could reflect group-level discursive practices or—due to the division of labor—individual students' practices. Nevertheless, the presence of these epistemic practices in the social setting of the classroom is noteworthy when planning pedagogical approaches and explicating learning objectives.

Conclusions

Technologies such as GenAI exert a substantial impact on the evolution of societies (Mishra et al., 2023). The fast and wide uptake of GenAI has sparked passionate discussions and debates about how educational institutions should respond, although far fewer discussions address this aspect. Debates on the short- and long-term implications of such decisions are much scarcer (McDonald et al., 2024).

Many existing suggestions for HE, such as GenAI assessment literacy (Moorhouse et al., 2023), emphasize the capability to design learning assignments that involve GenAI tools and provide students with opportunities to demonstrate genuine learning. TE, however, faces the task of developing ethical, research-based, and equitable pedagogical GenAI applications. In addition to understanding the operating principles of foundational models, future-proofing students requires pedagogical solutions that facilitate excelling in and consolidating various, continuously evolving, and changing sets of digital cognitive tools (GenAI, search engines, etc.) for optimized epistemic performance. In their future work, TE students might well face situations in which they will need to choose which GenAI-driven system will be suitable for their own pupils. *Foreseeing* society's educational needs is a challenge for TE.

For future-proofing, we suggest that TE should adopt a GenAI pedagogy that supports students' epistemic sensitivity in developing and maintaining hybrid intelligence—a competence that combines human decision-making and sensitivity to one's commitments (contexts, professional values, priorities, etc.) with an understanding of GenAI systems' capabilities, limitations, and ethical concerns. In practice, this entails the capability to combine the epistemic practices of Perry Positions 6–9 with the use of GenAI (and other future digital cognitive tools). This could be beyond many TE students' epistemic practices. Similar to half a century of research on students' epistemologies (Richardson, 2013), this small-scale research project suggests that TE should sensitively target students' many epistemological positions and scaffold the required epistemological transitions. Involving GenAI tools as a companion for hybrid intelligence requires TE teachers to acquaint themselves with GenAI tools and identify novel pedagogical approaches. Importantly, TE institutions should keenly, and in collaboration, promote finding suitable hybrid intelligence solutions by combining the wisdom of teachers' professional networks with reflections on TE learning objectives and pedagogical priorities. Placing the burden on individual teachers risks missing the opportunity that GenAI could provide for TE. Rather than maximizing epistemic shortsightedness—offloading epistemic effort for the production of mediocre term papers and theses—well-designed hybrid intelligence epistemic activities could push the current

standards of knowledge-building assignments up and support the cultivation of students' epistemic sensitivity.

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