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Citation for the original published paper (version of record):
Leino Lindell, T., Stöhr, C. (2026). The AI disruption in engineering education: an analysis of changing student norms through
cultural historical activity theory. Journal of Computing in Higher Education, In Press.
http://dx.doi.org/10.1007/s12528-025-09488-8

Journal of Computing in Higher Education
https://doi.org/10.1007/s12528-025-09488-8

The AI disruption in engineering education: an analysis of changing student norms through cultural historical activity theory

Tiina Leino Lindell[1] · **Christian Stöhr**[1]

Received: 17 September 2024 / Accepted: 17 December 2025

Abstract
This article explores the transformative impact of generative Artificial Intelligence (GenAI) on engineering education from a student perspective. Employing Cultural-Historical Activity Theory (CHAT), the study analyzes how GenAI challenges and changes established norms, and practices in and outside the classroom. Through thematic analysis of interviews with 25 students from a technical university in Northern Europe, we identify four themes of challenges or undergoing transformation due to GenAI: (1) the self-directiveness of students, (2) the objectives of learning, (3) the role of the teacher, and (4) the ethical aspects. The study reveals that participating students are developing new implicit rules for using GenAI to enhance their skills and understanding. These changes are driven by contradictions between traditional academic tools and the new expectations for self-directed and efficient learning support. While these students demonstrate awareness of GenAI's flaws and the challenges for academic integrity, they appreciate the immediate and personalized support provided by GenAI, which contrasts with the slower, more dependent nature of teacher interactions. This shift in expectations is leading to a re-evaluation of the division of labor between these students and their teachers. The study concludes by discussing the implications for the investigated educational practice and the potential development of theory, emphasizing the need for similar engineering education institutions to respond to the specific challenges and transformations observed in this context.

Keywords Engineering education · Students' norms · Generative AI strategies · Cultural-historical activity theory · Challenges and transformations · Contradiction

✉ Tiina Leino Lindell
tiinal@chalmers.se

1 Department of Communication and Learning in Science, University of Chalmers, Gothenburg, Sweden

Published online: 12 January 2026

Introduction

Higher education is currently confronted with significant challenges due to the increasing use of Generative AI (GenAI) tools, such as ChatGPT, among students (Huang et al., 2024). GenAI utilizes machine learning to detect patterns and generate new data based on training data. This technology can work with multiple modalities (text, image, audio), enable intuitive interactions, adapt to various tasks and contexts, and enhance productivity. However, Ronge et al. (2025) emphasize that the definition of GenAI should extend beyond these technical capabilities, as societal norms influence how GenAI is regulated and used. The perception of GenAI, including the hopes and fears associated with this technology, shapes our moral viewpoints, which in turn affect how we regulate its use, incorporating human morals and ethics into the definition. Since the launch of ChatGPT in the fall of 2022, students' norms and informal usage outside institutional design have raised substantial concerns about their potential to undermine academic integrity and fundamentally challenge traditional methods of designing and assessing academic tasks. In response, some universities have implemented stringent bans on AI tools to uphold academic standards and prevent cheating (Dempere et al., 2023; Grassini, 2023). Nevertheless, the impact of GenAI is not entirely straightforward, as research reveals a more complex picture. GenAI can lead to both positive and negative outcomes depending on its application (e.g., Rahman & Watanobe, 2023).

The complexity of GenAI's impact on education has been examined across various disciplines, yet engineering education stands out as both highly relevant and insufficiently explored in current research (Baig & Yadegaridehkordi, 2024; Batista et al., 2024). To begin with, engineering students engage with GenAI tools to a significantly greater extent than students in other fields, although uncertainty remains regarding what constitutes acceptable use (Stöhr et al., 2024). Engineering education is characterized by specific learning needs, such as solving complex technical problems and applying advanced tools and methods, which are areas where GenAI has demonstrated considerable potential (Devan et al., 2024). This potential is especially evident in subjects like programming, design, and embedded systems (Ariza et al., 2025; Batista et al., 2024; Mohammed et al., 2025). In addition, the interdisciplinary nature of engineering programs, which integrate knowledge from multiple domains, further enhances the relevance and applicability of GenAI in these educational contexts (Simarro & Couso, 2021). However, the integration of GenAI into engineering education can also disrupt traditional teaching methods and challenge established pedagogical norms (Devan et al., 2024). These conditions raise a critical question for engineering education: how can strategies be developed that balance the benefits and risks of GenAI usage while adapting to technological advancements and preserving academic integrity? As Baig and Yadegaridehkordi (2024) emphasize, a deeper understanding of the norms surrounding students' use of GenAI is crucial for crafting balanced and informed strategies for managing GenAI in academic environments.

Against this backdrop, this study investigates how 25 engineering students describe their use of GenAI in their studies and how this affects their educational practices. The students' accounts are interpreted as expressions of norms, understood here as ideas about what is considered legitimate, possible, or desirable in relation to

GenAI use in educational contexts. Drawing on Cultural-Historical Activity Theory (CHAT) these norms are conceptualized as *implicit rules* shaped through the interaction between individuals and their historical and cultural contexts. Norms are neither purely subjective attitudes nor externally imposed prescriptions; rather, they emerge through the dynamic relationship between subjects and the practices in which they are embedded (Engeström, 2001). A core principle in CHAT is the idea that "*contradictions* [are] *the driving force of change in activity*" (Engeström, 2001, p. 2). These contradictions are understood as systematic tensions or conflicts within an educational activity system. This theoretical perspective provides the foundation for the study's assumption that students' norms are shaped in response to the contradictions they encounter in their educational environments. As Engeström explains, "*as the contradictions of an activity system are aggravated, some individual participants begin to question and deviate from its established norms*" (ibid., p. 6). This passage illustrates how contradictions can prompt individuals to challenge established norms and contribute to the formation of new ones. As further elaborated by Engeström (2011), the introduction of new elements, such as technologies, into an activity system often leads to contradictions between existing norms and emerging practices, generating both disturbances and innovative attempts to change the activity. This insight is central to our analytical approach, as it frames students' access to GenAI as a potential source of such contradictions within educational practices. The relationship between norms and contradictions constitutes the analytical focus of the study. By offering a context-sensitive analysis of students' norms, the study aims to support engineering education institutions in understanding ongoing changes in educational practices and identifying key factors to consider when developing strategies for managing students' GenAI use.

Benefits and risks of GenAI use in higher education

Recent research highlights the dual impact of GenAI on student practices, emphasizing both its benefits and potential risks. Tools like ChatGPT are recognized for their potential to enhance learning outcomes when used appropriately, by providing personalized, immediate educational support (Campino, 2024). These tools generate cohesive, human-like responses, offering tailored assistance and challenges that match varying levels of student complexity (e.g., Adıgüzel et al., 2023). GenAI provides easy access to information through detailed, written responses rather than mere lists of sources, outperforming traditional search engines. Such capabilities not only boost self-improvement but also facilitate complex learning tasks, including language acquisition and programming (Farrokhnia et al., 2024), supporting the development of students towards a new identity as "spatially advised learners" (Ou et al., 2024). GenAI can recommend books and websites tailored to individual needs (Cotton et al., 2024) and provide educational resources such as study guides and lecture notes, enhancing students' grasp of course material (Perez et al., 2017). Furthermore, these uses of AI tools support scientific writing by improving communication and ensuring accuracy in non-native languages, thus helping students articulate their ideas more clearly (Lo et al., 2024). Singh et al. (2023) support this, noting that computer science students value ChatGPT for its ability to identify and correct writing mistakes, with additional benefits in code generation and debugging.

Students' use of GenAI raises several concerns. Bastani et al. (2024) argue that its impact on learning outcomes is uncertain. Additionally, it poses issues related to academic integrity and the establishment of new academic norms, including the risk of students submitting AI-generated work as their own (e.g., Mai et al., 2024). The development of norms that normalize such behavior could be exacerbated by the accessibility of AI tools and the limitations of current detection systems, which make it challenging to differentiate between original student work and AI-generated content (Mahrishi et al., 2024). Crawford et al. (2023) find that highly stressed students are particularly likely to adopt norms that justify AI misuse or lead to plagiarism. The research suggests that increased academic pressure, combined with the availability of technology, contributes to the formation of norms that make academic misconduct more prevalent. Farrokhnia et al. (2024) observe that students driven by superficial goals, such as quickly earning credits, tend to use AI differently than those genuinely invested in learning, potentially developing norms that prioritize expedience over deep learning. Therefore, fostering a mindful relationship with technology is crucial for effectively leveraging its educational benefits and shaping positive norms around its use. This perspective is supported by e.g., Cotton et al. (2024), who emphasize the importance of educating students about plagiarism and cultivating a strong moral character to prevent the misuse of AI and the establishment of harmful norms. Chan and Hu (2023) further argue that excessive dependence on AI can erode critical thinking and engagement, as students might develop norms that rely exclusively on AI-generated content rather than their own intellectual efforts. In contrast, Singh et al. (2023) find that students are aware of the risks associated with excessive reliance on GenAI, recognizing how it can weaken both critical thinking and investigative skills. Ngo (2023) points out frequent issues with the reliability of AI-generated information, including inaccuracies in references, which has led many students to advocate for norms that prioritize verifying AI responses against credible sources like scientific articles. The fact that GenAI content often contains biases and lacks deep theoretical understanding is a challenge frequently noted in research (e.g., Baidoo-Anu & Ansah, 2023), making it particularly problematic across disciplines such as medical education, mathematics, and software testing (Lo et al., 2024).

GenAI is changing the landscape of higher education

Research has mainly explored factors influencing students' use of GenAI, often through quantitative studies or theories grounded in the Technology Acceptance Model (TAM). For example, Baig and Yadegaridehkordi (2024) note that social influence, closely followed by perceived usefulness, is the most critical factor for ChatGPT adoption in higher education, emphasizing how social norms shape individual attitudes and behaviors towards technology use. While the usefulness of GenAI is acknowledged as valuable by students, gender, field of study, and academic level might also play a role (Stöhr et al., 2024). Chan and Hu (2023) identify that students' perceptions of GenAI have a profound impact on their learning methods. Positive perceptions often lead to norms that encourage deeper engagement and more effective learning strategies, while negative perceptions may result in norms that support surface-level learning. Students' attitudes thereby appear fairly diverse and complex: Stöhr et al. (2024) find that while most students have positive attitudes towards chatbots that make them more effective as learners, more than half also express concerns about their impact on education. They also show that while there is broad agreement that the usage of chatbots for assignment and exam completion is cheating, most students are also against prohibition.

In addition to these perspectives, research has begun to examine how the use of AI tools is reshaping social interactions and established practices within education. For example, Cotton et al. (2024) conclude that while the use of AI enhances peer learning and collaboration- offering notable advantages, particularly for students who cannot attend classes due to health issues- its integration also introduces new dynamics that affect the educational environment. Further, Carbonel and Jullien (2024) demonstrate in their quantitative study grounded in CHAT-theory, that the implementation of GenAI is transforming larger parts of the educational activity system. It alters students' learning objectives, prompts a re-evaluation of norms, and redefines the division of responsibilities between students and teachers. This growing reliance on GenAI for tasks traditionally managed by educators raises concerns about the quality of learning and the evolving role of teachers. The effectiveness of AI-generated feedback compared to teacher feedback remains uncertain and underexplored, further complicating the adaptation to these new norms (e.g., Crawford et al., 2023).

Identified research gap and study contribution

Although decades of research on formal AI systems in education, such as intelligent tutoring systems, have demonstrated significant learning gains, yang et al. (2025) emphasize that research on students' use of generative AI (GenAI) tools has only recently begun to emerge. Current studies primarily explore how students' informal use of GenAI impacts their learning practices, highlighting both opportunities and challenges (cf. Chan & Hu, 2023; Rahman & Watanobe, 2023). However, this body of work remains limited in several important respects.

First, there is a lack of qualitative studies of how students themselves perceive and negotiate norms around GenAI use in everyday academic contexts (Chan & Hu, 2023). Moreover, there is a need for empirically grounded insights into how students' perceptions are changing in response to GenAI (Wu et al., 2025), as well as a more holistic understanding of GenAI's influence on student engagement (Lo et al., 2024).

Second, many existing studies lack robust theoretical framing, which limits their ability to explain how students' norms emerge and evolve in relation to broader educational structures and institutional cultures (c.f. Baig & Yadegaridehkordi, 2024; Chan & Hu, 2023; Lo et al., 2024). As Granić (2025) points out, "*context-aware approaches when planning and evaluating GenAI adoption initiatives*" are essential, yet such perspectives are often missing from current research.

Third, research on GenAI in engineering education remains underrepresented, particularly in Northern European contexts, despite the technology's growing relevance in STEM disciplines and its widespread use among engineering students (Baig & Yadegaridehkordi, 2024; Batista et al., 2024).

To address these gaps, which include the lack of qualitative insight into student perspectives, limited theoretical framing, and the underrepresentation of engineering education in Northern European contexts, this study offers a qualitative, context-sensitive, and theoretically grounded analysis of how access to GenAI is reshaping engineering students' norms and educational practices. By contributing knowledge about the root causes of these transformations, the study highlights underlying dynamics that are important to recognize when addressing GenAI-related challenges in the specific local contexts examined.

Research aim and questions

This qualitative interview study, grounded in CHAT, aims to explore how students' access to GenAI influences the norms that govern their educational practices at a technical university in Northern Europe. By identifying contradictions that arise as a result of students' informal access to GenAI the study seeks to uncover key factors that must be considered when developing strategies for managing GenAI.

As mentioned in the introduction, within the framework of CHAT, norms are understood as implicit rules that regulate activity, while contradictions are historically and culturally situated tensions that arise when new elements, such as GenAI, disrupt established practices (Engeström, 1987; Virtaluoto et al., 2016). These contradictions are not merely conflicts but are conceptualized as drivers of change, revealing underlying tensions that can lead to the transformation of practices and implicit rules. Previous research in CHAT has shown that the introduction of new tools often generates such contradictions, which challenge existing norms and expectations (Engeström, 2001). By identifying contradictions, we understand the factors causing ongoing transformations that need to be addressed to develop informed strategies for managing GenAI in higher education. As Carbonel and Jullien (2024) and Nah et al. (2023) underscore, applying CHAT is crucial to grasp the dynamics within educational environments where GenAI is integrated. Nah et al. (2023) further argue that "only by situating the technology in a more holistic context of society, culture, and history can we fully understand the 'ripples' or outcomes it may bring. By addressing the contradictions that may arise from novel innovations within the activity system, society genuinely embraces such innovations and advances their potential to the fullest."

To investigate the research aim, the following research question is grounded in the CHAT framework, where contradictions are commonly used as analytical entry points in educational technology research (c.f. Murphy & Rodriguez-Manzanares, 2008):

- How do contradictions caused by generative AI challenge and transform the implicit rules and practices of engineering students in engineering education?

We continue with a short and necessary incomplete introduction to CHAT before presenting our methods and the findings.

Cultural-historical activity theory

This study adopts Cultural-Historical Activity Theory (CHAT) as its analytical framework to investigate how GenAI influences students' academic behaviors, with a particular focus on the norms that regulate their use of AI tools. CHAT is well-suited for this analysis as it provides a framework for understanding human actions within broader cultural, historical, and social activities. Additionally, CHAT offers an established approach to examining how the introduction of new tools, such as GenAI, transforms both the norms—i.e., the implicit rules governing the use of tools (Engeström & Sannino, 2021)—and the activity itself (Engeström, 2001, 2006).

CHAT, rooted in Vygotsky's concept of mediated actions (1978), posits that human thoughts and actions are mediated by the tools they use. This perspective was later developed by scholars such as Engeström (1987), who expanded it into a comprehensive framework for understanding human activities as socially and culturally mediated processes. In CHAT, the social and cultural context is understood as an activity system, which encompasses several key components:

- Rules: This component includes both implicit and explicit rules. Implicit rules include socially constructed norms that influence behavior within a specific context, such as people's expectations that guide actions without formal expression. In contrast, explicit rules are formally established and clearly communicated regulations, such as university policies on plagiarism or the guidelines and criteria set for assessments.
- Tools: The instruments and technologies, such as GenAI, that mediate and facilitate human action.
- Subjects: The individuals or groups engaged in the activity, such as students in an academic setting.
- Division of Labor: The allocation of tasks and responsibilities among participants within the activity system.
- Community: The collective of individuals who share common goals or are engaged in a similar activity, such as a classroom or academic institution.
- Object: The shared goal that motivates the activity, reflecting the participants' intentions and needs, which are rooted in the challenges they aim to address.

The components of an activity system are interconnected, as illustrated in Fig. 1. This interconnectedness implies that tools are embedded within contexts, and their implementation is shaped by human actors and decisions in social systems (May et al., 2023). Changes to one component can impact the entire system. For instance, the introduction of new tools like GenAI can challenge and alter established norms and practices within the activity.

According to CHAT, disruptions caused by new technology often lead to contradictions (Engeström, 2001, 2006). These contradictions arise when new elements challenge existing methods, creating tensions within the activity system. Specifically, these contradictions emerge when new practices conflict with established ones, driving systematic change (Engeström, 2006, 2009). For example, the integration

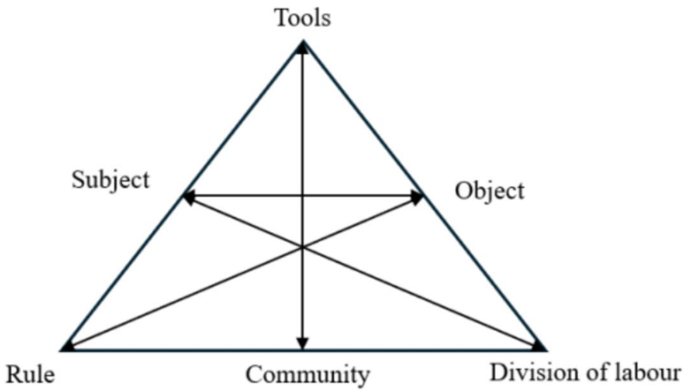

Fig. 1 Shows the activity system, its six components, and how they are related to each other (illustration inspired by Engeström, 1987, p. 78)

of GenAI into academic tasks may lead to a re-evaluation of how these tasks are approached. This can potentially alter the implicit rules that govern academic behavior, such as methods of completing assignments. Understanding how contradictions manifest as challenges and tensions within the components of an activity system provides critical insights into the factors that influence and shape the rules governing tool usage and how this, in turn, transforms the activity system (Sannino & Engeström, 2018; Virtaluoto et al., 2016). It is important to note that these contradictions are not merely obstacles. Rather, they reveal the core causes of transformations, i.e., the challenges people strive to address. Contradictions can also act as catalysts for future interventions, involving all actors in an activity system for the informed reconfiguration of challenging activities (Engeström, 2001; Miettinen, 2009).

Previous research utilizing CHAT illuminates the transformative impact of digital technologies within educational practices (Schuh et al., 2018). For instance, Van Horne and Murniati (2016) explore the motivations behind faculty adoption of ‘active learning classrooms’ designed to enhance collaborative learning and improve student outcomes. Czerniewicz et al. (2017) investigate how students’ practices and attitudes toward openness evolve within MOOCs. Kwong and Churchill (2023) analyze the contradictions arising from the implementation of ‘ePortfolio artifacts’, examining how these contradictions influence students’ motivations and behaviors. A notable example is students’ perception of the new ePortfolio system as inferior to external applications—a tool-related contradiction—that leads them to prefer external tools over the institution’s ePortfolio artifact for their learning activities.

The theoretical foundation and empirical studies exemplifying the application of the framework underscore the rationale for employing CHAT to elucidate how technological innovations impact students’ implicit rules and behaviors within educational practices, particularly through the lens of contradictions. This approach provides a deeper understanding of the mechanisms underlying the educational transformations driven by students’ access to GenAI. By examining contradictions, we can reveal the primary drivers of change that engineering education needs to consider when developing strategies for managing GenAI.

Method

To answer the research question, this CHAT-based, qualitative interview study examined students' perceptions of GenAI's impact on their learning practices. It combined one-to-one and group interviews, as recommended by Frey and Fontana (1991), to gain a deeper understanding of the investigated phenomenon. One-to-one interviews were chosen to capture detailed descriptions of individual students' attitudes and practices concerning GenAI (cf. Gubrium et al., 2002). This included their expectations of how GenAI could be used in engineering education, investigating implicit rules, and the challenges they aimed to address through their use of GenAI to understand manifestations of contradictions. Group interviews complemented individual interviews by allowing opinions to be shared and refined within the group, rather than relying on a single respondent's statement (Frey & Fontana, 1991). This approach helped to elaborate on and contextualize responses, thereby triangulating the qualitative data and enhancing the study's credibility (Elliott et al., 1999; Mathison, 1988; Yin, 2013). The data consisted of 11 one-to-one interviews and 6 group interviews. All interviews were audio-recorded, transcribed using *Whisper* software (an AI-based transcription tool), and then manually reviewed by researchers to ensure accuracy with the audio files.

All interviews were conducted as semi-structured interviews with open-ended questions, following the guidelines provided by Gaskell (2000). The questions focused on three main areas to collect data on students' norms regarding:

1. **If, how, and why students used GenAI**, which included the following questions: "Have you used AI, such as ChatGPT, for school assignments? If yes, please describe which AI technology you have used and how you have used it. What was the reason for using it for the school assignment?" The question regarding *why* students used GenAI aimed to uncover their motives for integrating GenAI into academic work. From a CHAT perspective, to provide insight into the *contradictions* students encountered within their educational activity system due to access to GenAI, and the *object* they formed in response (c.f. Engeström, 2001, 2006). The question regarding *how* students used GenAI was designed to capture how they addressed these contradictions in practice through their use of GenAI, and how this use contributed to the *transformation* of their educational activity system. This data was collected to address the part of the research question that asks: "*How do contradictions caused by generative AI challenge and transform the practices of engineering students in engineering education?"*
2. **Their perceptions of the advantages and disadvantages of GenAI**, which included the questions: "What do you think are the advantages/disadvantages of using GenAI for school assignments?" These questions were asked both independently and as follow-ups to their descriptions of how they use GenAI for school assignments. These questions were designed to elicit students' perceptions and reasoning, with a particular focus on how they formed *implicit rules* about the appropriate use of GenAI to support their academic *object*. This data was intended to address the part of the research question concerning: *"How do*

contradictions caused by generative AI challenge and transform the implicit rules of engineering students in engineering education?"

3. **Their awareness and reflections on any explicit rules regarding its use**, which included the questions: "What rules do you have at your educational institution regarding AI use? What do you think about these rules? What rules do you think should exist for AI use?" Since rules within CHAT encompass both implicit and explicit dimensions, these questions were posed to explore how GenAI influences not only students' informal norms but also their engagement with formal institutional regulations. Thereby, the intention was for the interview questions to contribute to answering the broader research question by enabling analysis of how contradictions challenge and transform both implicit and explicit rules within students' educational practices.

By structuring the interviews in this way, the intention was to generate qualitative data that enables analysis of how students' access to GenAI influences the norms that govern their educational practices at the technical university investigated. By collecting data on why and how students use GenAI, the aim was also to contribute to an understanding of the key factors that must be considered when developing strategies for managing GenAI. In this way, the interview questions were designed not only to address the research question, but also to support the broader aim of the study.

Sampling

In line with established qualitative research standards (Tong et al., 2007), we employed purposive sampling to select participants "*who share particular characteristics and have the potential to provide rich, relevant and diverse data pertinent to the research question*" (p. 351). To explore how contradictions caused by generative AI challenge and transform engineering students' implicit rules and practices, inclusion criteria required participants to be enrolled in engineering-related programs at a technical university in Northern Europe and to have experience using GenAI in academic contexts. In this study, students enrolled in architecture programs are included as engineering students, reflecting the institutional classification and the interdisciplinary nature of the programs at the technical university. To ensure variation in perspectives, we also applied a criterion that each data collection session included students from different programs and educational levels, aiming for diversity within each interview setting. Recruitment was conducted on-site, and students were included only if they represented a program or level not previously covered. Those without GenAI experience or not enrolled at a technical university were excluded.

For the group interviews, the method of natural groupings of students working together was applied, which involves using existing groups that naturally occur in their environments (Frey & Fontana, 1991). In this study, this method meant that the students who were approached had already grouped themselves to work together on school assignments that were not related to this study. Consequently, natural groupings were identified in public educational settings based on their existing collaborative work, ensuring that the group dynamics were authentic and reflective of their usual interactions. This approach resulted in groups of varying sizes and compositions, adhering to an established method to avoid researcher-driven group allocations. The aim was to foster conversations among individuals who were accustomed to working together, leading to more natural discussions about their experience and perspectives on GenAI.

Research site

This study was conducted at a technical university in Sweden, a country that stands out in Northern Europe for its internationally ranked engineering institutions (U.S. News & World Report, 2025). In addition, Sweden is recognized for its advanced digital infrastructure and high levels of digital literacy (OECD, 2018; European Commission, 2022). National surveys indicate that young adults, who represent the age group of most university students, are among the most frequent users of generative AI tools in Sweden (Internetstiftelsen, 2025). These contextual features make the Swedish engineering education environment particularly relevant for investigating how GenAI influences students' academic norms and practices.

Participants

This study involved 25 engineering students from a technical university in Northern Europe. Purposive sampling was employed (Cohen et al., 2007). All participants met the inclusion criteria defined for this study: they were enrolled in engineering-related programs and had experience using generative AI in academic contexts, thereby mitigating risks associated with coverage gaps (Tong et al., 2007; Twining et al., 2017). To ensure variation in perspectives, each data collection session included students from different programs and educational levels, Consequently, students from 13 different engineering-related subject areas were included, ranging from bachelor's to master's programs (See Table 1). The diversity of the participants' educational backgrounds as engineering students provides a broad representation of perspectives. Among the master-level participants, four were international students who primarily used English in their academic work, while all bachelor-level participants were fluent in Swedish. Interviews were conducted in either Swedish or English, depending on the participants' language preferences.

Data analysis

To answer the research question, reflexive thematic analysis (TA) was employed to identify patterns (themes) across the dataset (Braun & Clarke, 2021a), combining both inductive and deductive coding, following the guidance of Braun and Clarke (2021b). Reflexive TA differs from approaches that prioritize coding reliability and inter-coder agreement (e.g., codebook or content analysis). Instead of seeking consensus between coders, reflexive TA emphasizes the researcher's active role in interpreting the data, viewing subjectivity as a resource rather than a bias (Braun & Clarke, 2021a).

Table 1 Overview of data collection methods, students' program specializations, gender distribution, and number of participants

Data collection method	Educational programs (level)	Gender distribution	Number of participants
One-to-one interviews	Various bachelor and master programs in architecture, computer technology, community building, data science and AI, engineering and sustainability, electrical engineering, embedded electronics system design, mathematics, mechanical engineering, production engineering, technology and design	Male 8, Female 4	12
Group interviews	Bachelor programs in architecture, architecture and technology, automation and mechatronics, computer technology, mechanical engineering	Male 6, Female 7	13

In the first step, two researchers jointly reviewed transcripts while listening to the audio recordings. Through inductive coding, we identified similarities in students' attitudes and practices, focusing on how they described their access to GenAI as influencing their educational practices at technical university. This process resulted in three preliminary themes.

One researcher then conducted semantic-level inductive coding of all transcripts (see Braun & Clarke, 2021b for semantic coding), focusing on what students explicitly said about how they used and expected GenAI to be used. For example, if students described "using GenAI to help brainstorm ideas, instead of bouncing ideas off each other because it generates many more ideas compared to slow interpersonal conversations," this could be categorized as 'enhancing idea generation.' These codes were subsequently clustered into semantic code groups within each preliminary theme to capture patterns in how they aligned with the overarching themes. A full overview of themes, semantic code groups, code examples, and illustrative quotes is provided in Appendix 1.

In the next phase, the same researcher conducted a deductive analysis, where the original quotes within the inductively identified themes were analyzed in relation to the components of CHAT's activity system, based on the advice of Sannino and Engeström (2018) and Virtaluoto et al. (2016). The example of students using GenAI to 'enhance idea generation' analyzed in relation to the activity system indicated that they had an *implicit rule* about the *tools* used in the ideation phase. This shifted their *object* from purely human-generated ideas to a hybrid approach integrating AI suggestions with a motive of being efficient. It also indicated that the collaboration among people had decreased, i.e., their *division of labor* had changed.

To further understand how these ongoing transformations were triggered by *contradictions* caused by GenAI access, a follow-up deductive analysis was conducted with the activity system components. In this analysis, we highlighted the reasons students described for using GenAI, i.e., the challenges they aimed to address through its use. Their *object* indicated that their motive for using GenAI was its efficiency compared to human efforts. The capabilities of a traditional *division of labor* with purely human idea generation thus struggled to support these new demands, which triggered students to use GenAI for idea generation. This example highlighted how contradictions were analyzed as tensions between the components of the activity system—students' *new object* and the limitations of the traditional *division of labor*—and how these contradictions drove transformation. This approach to identifying contradictions followed the recommendations of Sannino and Engeström (2018) and Virtaluoto et al. (2016).

Once the deductive analysis was completed, both researchers collaboratively reviewed the results. During this review, we noted that some quotes initially grouped under the first theme were not grounded in the same type of contradiction. This led to a revision of the thematic structure and the identification of an additional theme. The relevant semantic codes were re-clustered accordingly. This process illustrates the iterative nature of reflexive thematic analysis, where theme development is revisited and refined through ongoing engagement with the data and theoretical reflection (Braun & Clarke, 2021a). Through this analysis, we gained insight into how students' access to GenAI is transforming implicit rules and practices in engineering education. Through this analysis, we could understand how students' access to GenAI was transforming engineering students' implicit rules and engineering education practices.

Findings

Overall, the findings demonstrate that the participating engineering students are integrating GenAI to enhance their skills and understanding. This integration transforms several elements of the activity system, as observed within the context of a technical university, impacting engineering educational practices. Our analysis identifies four key areas of transformation:

- *GenAI transforms students' Self-directiveness and efficiency*—Defined by students' descriptions of how they used GenAI to independently manage their learning processes, and to save time and handle workload efficiently.
- *GenAI challenges the objectives of learning,*—Defined by students' descriptions of using GenAI in education in ways they perceive as preparing them for future labor market tasks and employer expectations.
- *GenAI changes the role of teachers*—Defined by students' accounts of using GenAI instead of interacting with teachers, or in ways that affect teachers' work.
- *GenAI challenges the ethics of cheating*—Defined by students' descriptions of how GenAI is used in ways they perceive as acceptable or unacceptable.

To provide context for the types of tasks these students describe using GenAI for, across these four categories, see Appendix 2 for an overview of the student-reported

GenAI use. The study addresses the research question by exploring these four areas of ongoing transformations, including the participating students' implicit rules, along with the contradictions that drive this transformative process, in detail below.

GenAI transforms students' self-directiveness and efficiency

The finding suggest that the participating engineering students' access to GenAI is reshaping their implicit rules regarding self-direction and efficiency with academic tools. This transformation appears to be driven by contradictions between their object of enhancing understanding and skills through self-direction and efficiency, and the limitations of traditional educational tools in fulfilling these needs (See Fig. 2).

Several students described using GenAI to address specific challenges they face with academic tasks, particularly in writing essays within engineering subjects. For instance, one student turned to AI to tackle writing difficulties and noted: "*OK, I have to be honest. I'm really bad at writing. Like, incredibly bad. So, it was really great that I found this.*"

This quote proposes that GenAI was used as a compensatory tool to address perceived deficits in writing ability. The student's use of "really bad" and "great that I found this" signals a strong contrast between their previous struggles and the perceived support GenAI offers. He further elaborated:

> I've noticed that I have become better at writing. […] when I write, it becomes more nuanced, and I use a wider variety of […] synonyms. I can understand more of the synonyms and, since I can still sense what is AI-generated, I can take that inspiration and write in a similar way, but still keep it human. When I get inspiration from AI, I find that high-quality word I might have missed before.

This elaboration shows how GenAI not only supports task completion but also fosters deeper engagement with language. The student's ability to "understand more" and "take inspiration" suggests increased self-direction in learning. The phrase "missed before" points to previously inaccessible linguistic tools, indicating a contradiction

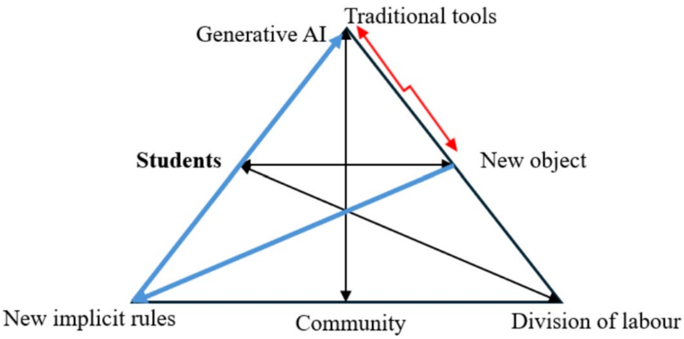

Fig. 2 Shows how a contradiction between traditional tools and students' new object of self-directed and efficient personal growth triggers changes in their implicit rules for tool usage to achieve this object

between the student's evolving learning goals and the limitations of traditional tools. This contradiction triggers a transformation in the activity system, where GenAI becomes a legitimate part of the division of labor and mediating tools, reshaping implicit rules around academic writing and learning autonomy. Similar patterns were described by another student who used GenAI to overcome challenges in understanding concepts and developing problem-solving skills:

> The advantage is that it's like a search engine that can handle slightly more human inputs. You can sort of say what you think, and it will understand you, instead of Google, which might just look for specific words and so on.

This quote illustrates how GenAI enables the student to more easily manage information independently, indicating increased self-directiveness in the process of seeking factual knowledge. Note that both examples refer to tasks that could have been addressed by technological tools (such as Google or the synonym function in MS Word) even before the GenAI popularization. This shift underscores how the limitations of traditional tools and the easy-to-use nature of GenAI tools such as ChatGPT lead many students to prefer AI, which offers a more intuitive and personalized approach to information retrieval. Thus, the citations from this group of engineering students exemplify the contradiction between students' new learning object and the limited capacity of traditional tools to meet them, triggering new expectations (new implicit rule) for support and a preference for using GenAI in tasks.

GenAI also addresses most of the students' new expectations for efficiency. One student explained:

> as an engineering and technical sciences student, […] you needed to analyze large amounts of data and numbers, which you really could not do manually […], even though Excel and other tools like BIS and tablets are useful. While these data visualization and configuration tools were good, none could process data at the speed that ChatGPT did. Because of its NLP capabilities and various language modules, ChatGPT could handle this much faster. […] you should be familiar with it and use it, but only to the extent that it helped you diversify your ideas.

This quote suggests that this particular student's object of efficient data analysis and idea generation was not fully supported by existing tools. The comparison with platforms like Excel suggests a contradiction within the activity system: the student's expectations for speed, adaptability, and intuitive interaction exceeded what these tools could offer. GenAI's capabilities reconfigure the tool component, prompting a transformation where AI is integrated as a necessary mediating artefact. The student's emphasis on speed and idea diversification also reflects increased self-directiveness in managing workload and learning strategies.

In short, the findings from this group of engineering students show that they are increasingly integrating GenAI for their personal growth due to its ease of use and efficiency compared to traditional educational tools. Consequently, they have developed implicit rules for using GenAI to enhance their learning and skills in a self-directed and efficient manner.

GenAI challenges the objectives of learning

These findings suggest that the participating students' access to GenAI might transform the goals of learning within the engineering education context studied. These engineering students now view mastering GenAI as crucial as acquiring other engineering skills. This shift is not only driven by the inadequacies of traditional tools and the need to develop effective AI usage skills, but also by an appreciation of changing labor market requirements (See Fig. 3). One student noted about GenAI:

> You'll use it for almost everything at work [...] There's often time to be saved, and you can apply it to anything you feel you need it for. I don't think employers would mind; it's just another skill, like being good at programming or math. In the workplace, what really matters is how efficiently you can get the job done.

This quote illustrates how this student's object, what they need to learn and which tools they need to master, is shaped by concerns about future job market demands. The comparison with other skills such as programming and math reflects a contradiction between established educational goals and emerging expectations for workplace efficiency. GenAI's perceived relevance reconfigures the rule component of the activity system, prompting a transformation in what is considered legitimate learning, with GenAI becoming a central tool in that process.

We also identify widespread uncertainty and concern regarding changing expectations on competences and about a potential over-reliance on AI. As one student in architecture expressed:

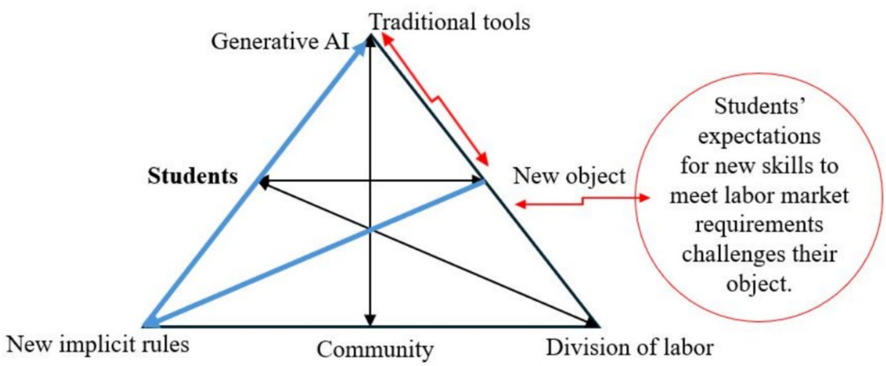

Fig. 3 Illustrates how students' object for what they need to learn and which tools they need to master are challenged by their concerns about future job market demands, this contradiction prompting some students to use GenAI

> How dependent will I become on AI? Will I suddenly be expected to design, for example, six buildings because I can use AI, instead of just one in the same amount of time? I still want to be proficient with all the tools that the workplace expects or requires.

These concerns reflect the uncertainty about potentially shifting norms about what GenAI competences are essential for overcoming the limitations of traditional tools and adapting to evolving career demands. Within the CHAT model, this doubt not only limits the formation of a new object regarding what these students need to learn, but also affects the implicit rules, creating uncertainty about whether they should use GenAI.

Together, these findings expand the shifting roles of digital tools for personal growth and self-directiveness identified in the first theme and indicate contradictions manifesting in a potential new object of the learning process that includes GenAI competences as a central component for future careers among the participating students across most engineering programs.

Gen AI changes the role of teachers

The findings indicate that the participating engineering students' evolving implicit rules for integrating GenAI into academic practices are transforming teacher-student interactions and challenging the role of teachers. This shift is triggered by contradictions between students and teachers in the activity system, manifesting in two key areas. The first contradiction is evident in the tension between students' new object and implicit rules for using GenAI and the division of labor (See Fig. 4). The second contradiction manifests as tensions between teachers' and students' differing views on how GenAI should be regulated, as well as students' uncertainty about the explicit rules (See Fig. 5).

Firstly, as previously described, these students' access to GenAI appears to be reshaping their expectations for self-directed and efficient support. This shift influences not only their learning object but also their interactions with teachers:

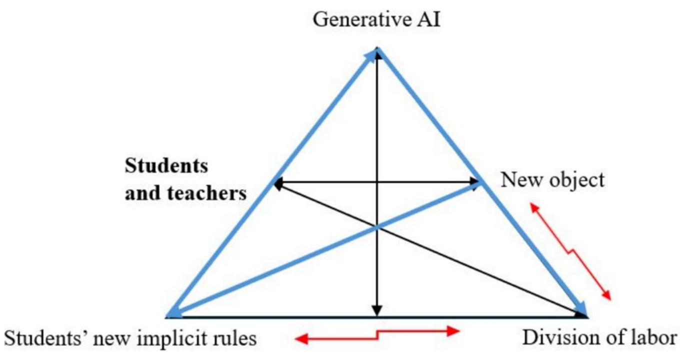

Fig. 4 Illustrates the contradiction between students' new object and implicit rules for tool usage versus teachers' roles within the division of labor. This contradiction affects how students use GenAI and interact with teachers

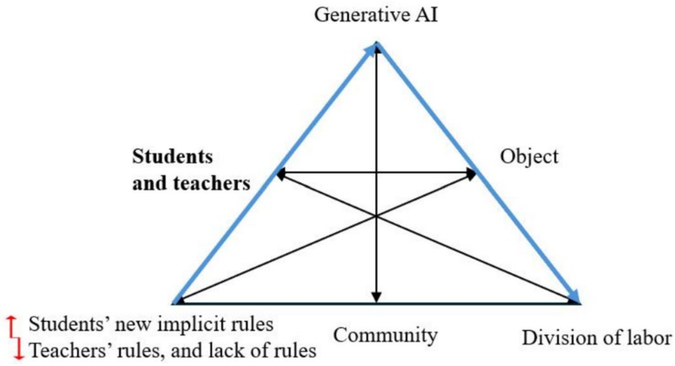

Fig. 5 Shows how contradictions between students' new implicit rules for GenAI use and teachers' rules, or lack thereof, affect students' GenAI usage and their interactions with teachers

> Often, it takes longer to ask the teacher, and ChatGPT gives immediate answers. Often, you want to try to understand it yourself. By using ChatGPT, it feels like you've figured it out on your own. But if you ask the teacher directly, you might get an answer that you want to have more of a back-and-forth dialogue with, which you can't do in the same way. And then it doesn't feel like you've come up with the answer on your own.

This quote points to a key shift: the student describes valuing the immediacy and self-directed support that GenAI provides, in contrast to the slower, more dependent nature of teacher interactions, which some students can find challenging. It exemplifies the contradiction between students' new expectations for support (object and implicit rules) and the teachers' limited capacity within their roles to meet these expectations (division of labor). This transformation, marked by reduced interactions between teachers and students, is further illustrated by another student expressing new expectations for timely support:

> I don't often go to the exercises because they are very early in the morning, and sometimes I have questions for TA, but now I can just ask the questions to ChatGPT instead. Then you usually get very good answers. [...] I don't need to be present at every exercise. Yes, it is very time-efficient.

This example highlights how this student uses GenAI to bypass the contradiction between their new expectations for timely support (object), and traditional academic routines including the challenges of getting prompt answers from teachers (division of labor). The resulting implicit rule is that GenAI is now considered a legitimate and flexible tool for learning support that fits their personal schedules, which sometimes means relying solely on GenAI to understand presentations instead of attending in-class activities. NOTE: While AI facilitates quick answers and reinforces basic understanding, several students still recognize the value of teacher interactions for more complex, nuanced discussions: "*But if you have a specific problem-solving task to do in a certain context, then the teacher is usually better. But for general informa-*

tion, AI is better and more convenient.” This excerpt shows how these students are balancing AI’s utility for straightforward queries with the deeper insights provided by teachers, illustrating their preference for AI when it better meets their learning needs than teacher support.

Secondly, the participating students’ access to GenAI creates new unresolved tensions in the interactions between teachers and students potentially influencing how teachers carry out their work. One student describes this transformation as follows:

> For example, you might write a bullet list, ask ChatGPT to create a sort of template for it, and then rewrite it so that it reflects ChatGPT’s structure but with your own words and understanding. I personally think that’s okay. Teachers are not always super clear about this. Most might say, for example, that ChatGPT is completely forbidden, or that ChatGPT can be used but calculations will be verified by the teachers themselves. So there is, in my opinion, a difference. [...] I really think it’s hard to stick to those rules because it feels a bit unreasonable to me, given that this is a technical university where you need to develop alongside the technology. And if you can use ChatGPT and AI tools in a way that helps both students and teachers, you should try to find a solution that benefits both.

This example illustrates how this student’s new implicit rule of using GenAI to generate a template and then reworking it with personal understanding conflicts with the formal rules imposed by teachers. This manifests an unresolved contradiction between different rule systems within the activity, affecting interactions between students and teachers, leading to ongoing tension over rule formation and implementation. Some of the participating students mentioned how GenAI has led to iterations of new rules from teachers and adaptive (unintended) changes in student behavior:

> They’ve started to notice patterns of what’s AI-generated and what’s human-made. [...]you can tell they grade differently now. It’s more honest. So, we adapt as well. [...] Now, I still take inspiration and write in a similar way, but in a way that feels more human.

This quote indicates a contradiction, as teacher-imposed rules have led to adaptive counter-norms guiding these students’ use of GenAI in ways that blur the line between human- and AI-generated work. This contradiction also affects the division of labor, as teachers are tasked with enforcing rules that the student in the quote describes increasingly circumventing through new practices, which in turn makes assessment more complex. Another student highlighted the need for teachers to adapt instead of creating restrictions that cannot be enforced: “*I think it’s more about improvement for those teachers whose questions can simply be fed into ChatGPT—they may need to refine their assignments rather than impose restrictions that can never truly be enforced.*” This suggestion that teachers reconsider assignments, since students can circumvent existing requirements, manifests a contradiction between students’ and teachers’ rules and signals some students’ desire for change in how teachers carry out their work, particularly regarding the design and clarity of assignments in relation to GenAI use.

To conclude, the participating students' use of GenAI reduces teacher-student interactions when performing generalizable tasks. This tendency was observed among engineering students in this study and appears to be driven by a contradiction between students' new object and implicit rules for seeking self-directed and efficient support for personal growth and teachers' limited capacity to meet these new expectations. Additionally, the use of AI creates ongoing tensions between teachers and students, triggered by their differing rules governing AI usage.

GenAI challenges the ethics of cheating

The participating engineering students' access to GenAI challenges established norms of ethics and academic integrity in relation to other norms within the activity system. The prior sections outline how these students have developed implicit rules for using AI to enhance their understanding and skills in a self-directed and efficient manner. However, they also show broad awareness of GenAI's flaws and biases. One student explained:

> "Very often, it feels helpful to discuss a new concept with someone. And I think AI works very well for that, especially since you are aware that it can be wrong, and in some way, it's reassuring that it can be wrong. Because it means you have to double-check everything, and it becomes more of a natural conversation than just, here, you have the right answer. That's probably what I find ChatGPT most useful for."

This quote exemplifies how the student not only exercised caution in trusting the generated answers, but also utilized these inherent potential biases for their learning process. It illustrates how GenAI is seen as acceptable when it stimulates reflection rather than replaces it. Similar views were expressed by other students, as one student noted: *"We cannot use this software for making reports. Our assignments are tasks we need to do ourselves; otherwise, we can't understand the content."* Another said: *"Just directly copying outputs from ChatGPT, that's essentially cheating. You need to be able to reason through what you write."*

These quotes show how some of the participating students value personal reflection in their work, viewing extensive automation with GenAI as a violation of their rules. A few students even advocated full AI transparency in their assignments. Interpreted through the lens of CHAT, such implicit rules can be understood as emerging in response to contradictions between students' learning object and GenAI's limitations and possibilities. When GenAI offers overly polished or inaccurate answers, or enables shortcuts that undermine learning, these students respond by negotiating norms that balance technological support with academic integrity.

However, the efficiency of GenAI sometimes leads some students to deviate from their implicit rule of using it to support rather than replace learning. A contributing factor to this shift appears to be time constraints and workload, which influence how they apply GenAI, particularly when tasks are perceived as less meaningful or urgent. One student described this phenomenon:

> Generally, when using AI, specifically ChatGPT, it's mainly because of time constraints. People are willing to work thoroughly on important tasks, but for less significant ones, AI takes over. For challenging tasks, AI might not perform as well. It's really for courses you're not interested in at all.

Additionally, several students have reported that exhaustion and a sense of laziness, combined with the new possibilities of AI, have led them to prioritize automation over learning. Another student explained how GenAI's efficiency has led to increased last-minute work: "*it becomes more and more last minute. You know it might take a day without ChatGPT, but with ChatGPT, it takes two hours. So, when it's two hours before the deadline, you just go for it.*" This observation illustrates how the efficiency offered by GenAI can contribute to procrastination. The ability to quickly complete tasks with AI creates a time crunch, which may lead some students to deviate from their implicit rules. Interpreted through CHAT, this behavior reflects a contradiction between students' division of labor in relation to workload and GenAI's capacity to enable efficiency and prioritization of automation. This contradiction prompts them to renegotiate their ethical boundaries between academic ideals and practical constraints (See Fig. 6). This issue can be further worsened if students lack subject knowledge, making them unable to critically assess AI-generated content, as several students noted.

Another aspect that influences the participating students' ethical reasoning around GenAI use concerns the rules communicated by teachers. Several of them described how unclear or restrictive regulations can lead to frustration and uncertainty about what constitutes acceptable use. As one student explained: "*I just think it will be harder to forbid it. Then it will become a kind of competition between students who want to exploit it in a bad way and the rules that try to stop it.*" This quote illustrates

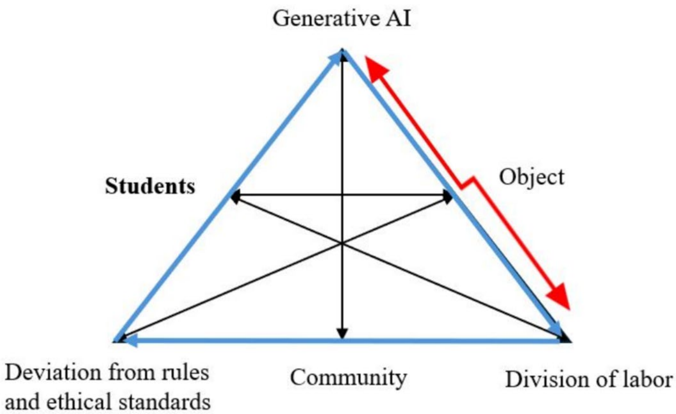

Fig. 6 Shows how students' workload (division of labor) and new task-streamlining opportunities from GenAI create contradictions, leading some to reprioritize their implicit rules and use GenAI in ways that conflict with their ethical standards to better manage their time and tasks

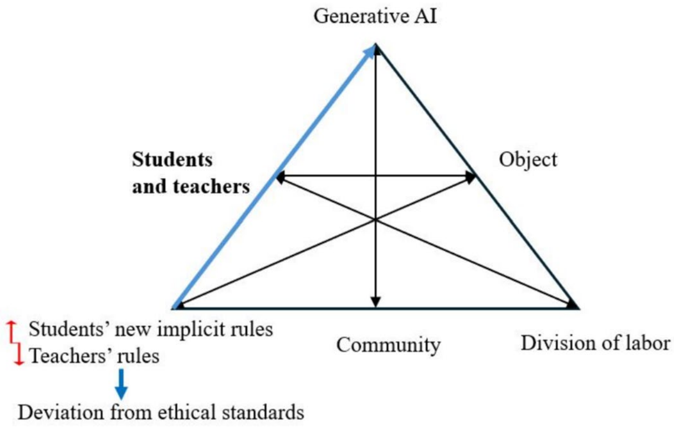

Fig. 7 Illustrates how contradictions between students' and teachers' rules can trigger students to use GenAI in ways that deviate from their implicit rules

how conflicts over rules can be counterproductive, potentially driving students to develop methods to circumvent these rules, thereby contradicting their own standards for acceptable use. Interpreted through CHAT, this behavior reflects a contradiction within the rule component of the activity system, where these students' evolving implicit rule for how tools can be used to support the learning object clashes with institutional attempts to regulate GenAI. As a result, they may renegotiate their ethical boundaries and develop informal norms that extend beyond their own perceptions of fairness and relevance (See Fig. 7).

In summary, the use of GenAI is putting established ethical norms in question. While the participating students initially adhered to principles of personal involvement, constraints in the division of labor and the efficiency of GenAI reflect how they reevaluate the existing norm structure, balancing ethical considerations with practical needs, often prioritizing tasks they themselves perceive as meaningful.

Discussion

In the following, we will highlight and discuss the main contributions of our findings as well as implications of our findings for teaching practice and research. This study's primary contribution is providing a context-sensitive, qualitative insight into how students' access to GenAI may be influencing educational practices within a technical university setting. By examining how access to GenAI influences students' norms that regulate their behaviors, our analysis identified four key transformation areas and the contradictions that catalyze these changes. In doing so, we draw attention to core issues that are crucial to consider when developing strategies for addressing GenAI. While these findings are situated within a Northern European technical university, they may offer indicative insights for other engineering education contexts with similar characteristics.

Practical implications

Firstly, our findings show that the participating students are motivated to use GenAI primarily due to its ease of use and efficiency, surpassing traditional tools. This aligns with other studies of GenAI adoption in education that build on theories such as the Technology Acceptance Model (TAM) that highlight usability and perceived usefulness— particularly of tools like ChatGPT (Baig & Yadegaridehkordi, 2024; Stöhr et al., 2024). The findings suggest that these students now expect personalized, flexible, and adaptive learning support, which echoes earlier findings (Campino, 2024; Cotton et al., 2024). This includes GenAI's effectiveness in helping students grasp course material (Perez et al., 2017), providing tailored information (Farrokhnia et al., 2024), and offering support in scientific writing (Lo et al., 2024) and coding (Singh et al., 2023). However, it is important to note that our findings refer to student expectations in a context where GenAI tools are used informally and outside institutional design. Therefore, we cannot determine whether students' learning was actually enhanced in practice. It is important not to generalize these perceptions as evidence of learning effects, especially since some research contradicts this assumption (e.g., Bastani et al., 2024).

In either case, our findings from this specific group of students imply that academia faces challenges in reversing this trend unless they offer equally effective tools to meet these new demands. Additionally, our findings suggest that some of the participating students' learning objectives in engineering education are transitioning due to their shifting expectations and uncertainties regarding future job market requirements. As Stöhr et al., (2024) highlight, students are not only excited but also challenged by concerns about GenAI's impact on education. In our study, several students reflect on how GenAI transforms professional practices across various fields, challenging them to evolve their competencies accordingly. These reflections and skill developments often occur ahead of formal curricular changes, suggesting that engineering education institutions may need to consider not only address the ethical use of AI for learning, but also integrate AI literacy related to the particular professional fields into their programs to prepare students for the practical realities of their professions, which are being reshaped by AI.

Further, our study, like Carbonel and Jullien (2024), provides evidence that GenAI is not just a means for students to accomplish tasks more efficiently; its use is actively redefining the student–teacher relationship. In terms of CHAT, GenAI functions as a mediating tool, as students' access to it not only disrupts the "subject-object" relationship between students and their learning goals but also challenges established "rules" and the "division of labor" within educational settings. These evolving student–teacher roles highlight how some students in our study perceive the benefits of feedback from GenAI compared to that from teachers. This shift not only alters remote working methods for those with health issues, as noted by Cotton et al., (2024), but may also contribute to decreased in-person attendance among a broader population of students who discover new ways to use tools to replace interactions with teachers. This finding enriches our understanding of an area previously identified as underexplored (Crawford et al., 2023; Farrokhnia et al., 2024), adding insights to current knowledge. These contradictions involving teachers' division of labor and rules create ongoing uncertainties and tensions that teachers need to address. Specifically, the observed rule contradictions highlight new demands from students for changes in teaching roles. A suggestion is to engage in open and inclusive discussions with students to develop a shared understanding of acceptable use.

Another important finding from our study is the broad awareness among the participating students of the ethical concerns and potential risks associated with GenAI, despite the lack of explicit guidance at many universities (Stöhr et al., 2024). While Chan and Hu (2023) observed that excessive dependence on AI can erode critical thinking and engagement, this study, like that of Singh et al., (2023), showed that several students are aware of the importance of their engagement for AI to support learning and the risks of automation. Previous studies have demonstrated how students' positive and negative perceptions (Chan & Hu, 2023), gender, field of study and academic level (Stöhr et al., 2024) influence how they use GenAI. Our study suggests that it is students' learning goals combined with their "division of labor" that determine when they use AI for learning and when they choose to automate their tasks to ease their workload. In this way, the findings echo Crawford et al., (2023), who found that highly stressed students are particularly likely to adopt norms that justify AI misuse or lead to plagiarism, and Farrokhnia et al. (2024), who noted that students can use GenAI for both cheating and learning. Our study contributes by illustrating how GenAI may function as a tool that enables students to prioritize their time and tasks, they find meaningful within their specific educational context. This agency over task prioritization might explain why students in Stöhr et al., (2024) found that most students are against prohibition, despite the risk of cheating.

Based on the findings presented here, we see indications in some students' descriptions that calls to educate students about plagiarism and cultivating a strong moral character to prevent AI misuse (e.g., Cotton et al., 2024; Farrokhnia et al., 2024) may increasingly need to account for the competitive academic pressures and shifting norms that students are navigating. The findings indicate that some students in this study seem to act with considerable awareness in this behavior. Rather than a general lack of AI literacy, we found that these students feel compelled to act rationally, as those who use GenAI may gain advantages over those who do not. These dynamics could potentially lead to system changes including higher assessment standards, greater academic pressure and ultimately increasing inequalities. These dynamic risks may marginalize students who are more cautious about AI use, as they may struggle to keep pace with peers who embrace GenAI more readily. Students' conscious behavior and the need to automate tasks to reduce their workload make it likely that some students continue to submit automated AI-generated work as their own (e.g. Mai et al., 2024), especially given the difficulty in detecting such content (Mahrishi et al., 2024) and the generalizability of tasks. Note, that this study focuses on the factors driving engineering students' norms, not the difference between basic knowledge of plagiarism and a comprehensive level of AI literacy. Established AI literacy, including ethical decision-making, could still provide a foundation for balanced and moral AI use. These findings suggest that teachers should aim to assign tasks that resist easy generalization and promote meaningful learning to mitigate the risk of misuse. However, with the current speed of GenAI progression, the goal of generalization appears to be a moving target. For example, Adıgüzel et al., (2023) found that AI can handle various levels of complexity.

Our research introduces additional nuances to the advantages and disadvantages of GenAI highlighted in previous studies. The students in this study appreciate not receiving ready-made answers and accurate information about concepts, as they believe these fosters increased engagement and learning. This adds an important perspective to the majority of research that reports inaccurate GenAI-generated information as an unidimensional negative aspect for learning (Baidoo-Anu & Ansah, 2023; Lo et al., 2024; Ngo, 2023). Insights like this may be attributed to the qualitative approach chosen for this study, which provides nuances that previous quantitative research on GenAI (Lo et al., 2024) may have overlooked.

Limitations

This study has some limitations that should be acknowledged and that point at needs for future research. First, while the study focuses on how contradictions caused by students' access to GenAI influence the norms that regulate their educational practices, aligned with the CHAT framework, it does not investigate students' motivations for choosing one GenAI tool over another. This omission reflects a theoretical limitation within activity theory itself: although CHAT provides a robust framework for analyzing how tools mediate activity and how contradictions drive change, it does not offer conceptual tools for explaining why individuals select specific tools over others.

Secondly, our analysis focused on contradictions that trigger implicit rules for GenAI use but did not explore cases where implicit and formal rules align. It is also important to acknowledge the limitations regarding the transferability of these findings. While the study offers insights into GenAI use among engineering students at a Northern European technical university, these findings may not fully translate to other educational contexts. Another limitation lies in the scope of the study's focus on student perspectives. While students' views are valuable in understanding how access to GenAI is shaping learning practices, the study does not include the perspectives of other key stakeholders, such as educators, program heads, and educational administrators.

Methodologically, the study relies primarily on qualitative data from 25 engineering students, which provides rich context-specific insights into student behaviors and perceptions but it also limits the generalizability of the findings to other contexts. In addition, the study's temporal scope is limited, as it provides a snapshot of these current student behaviors and attitudes toward GenAI. Given the rapid pace of AI development and integration in education, these behaviors and tensions may evolve quickly.

Future research

Future research could usefully explore the motivations and barriers among non-users providing a more balanced understanding of GenAI adoption. It would also be valuable to examine how alignments or misalignments between implicit and formal rules impact learning outcomes and the broader educational system. Taking a multi-stakeholder approach, including educators, program heads and administrators, may offer a more holistic view of GenAI integration. Additionally, longitudinal research could help track how student practices, institutional policies and educational norms evolve over time as GenAI become more embedded in engineering programs and other disciplinary settings.

In relation to the theoretical limitations discussed, future research could also explore ways to extend CHAT by integrating it with complementary frameworks such as TAM or UTAUT. Despite epistemological differences, such combinations may offer valuable insights into students' tool selection and perceived usefulness, that is dimensions that CHAT does not explicitly account for. Moreover, our findings suggest a potential link between GenAI use and CHAT's levels of human procedures: operations (automated actions), actions (goal-oriented problem-solving), and activities (collective efforts toward complex objectives) (cf. Engeström et al., 1999). Further research could explore whether and how GenAI supports task automation at the operational level, individual goals at the action level, and complex problem-solving and collaboration at the activity level. It seems there is a connection between these levels and the extent to which tasks are automated from human to GenAI.

Conclusion

Using Cultural-Historical Activity Theory, the key findings from the study highlight the contradictions that drive student norms within the studied engineering context regarding their use of GenAI. We identify four key areas of transformation:

- *Students' self-directiveness and efficiency* are being reshaped due to contradictions between traditional educational tools and students' new object of self-directed and efficient personal growth. This leads to changes in their implicit rules for tool usage.
- *The objectives of learning are challenged* as students' perceptions of what they need to learn, and which tools they need to master, are influenced by anticipated labor market demands. This contradiction prompts some students to integrate GenAI into their learning strategies.
- *The role of teachers is changing* due to contradictions between students' expectations for autonomy and efficiency and the traditional division of labor in education. Additionally, tensions between students' implicit rules for GenAI use and teachers' formal or unclear rules affect how students interact with educators.
- *The ethics of cheating are challenged* as contradictions arise between students' workload and the efficiency GenAI offers. This contradiction lead some students to reprioritize their implicit rules, sometimes in ways that conflict with academic integrity. Further contradictions between institutional rules and student norms also contribute to this shift.

By identifying these transformations and contradictions, educational stakeholders can gain a deeper understanding of how GenAI is transforming engineering education and the underlying reasons behind these changes. Understanding the root causes of students' behaviors is crucial for engineering education to initiate transformative efforts where problematic use is addressed collaboratively across all levels of education. Established intervention methods within Cultural-Historical Activity Theory research can be utilized for such processes, providing opportunities to develop strategies for GenAI that consider both its potential and challenges (Engeström, 2001). While it is clear that GenAI brings substantial challenges and transformations, it is still too early to determine whether these changes will be disruptive for engineering education as a whole. Continued research and observation will be crucial to understanding and managing these ongoing transformations.

Appendix 1: Overview of themes, semantic code clusters, code examples and illustrative quotes

Theme	Semantic code clusters	Examples of semantic codes within clusters	Quote examples
Self-directiveness and efficiency Students' descriptions of how they used GenAI to independently manage their learning processes, and to save time and handle workload efficiently	Students using GenAI to: Deepen their understanding, including concepts and factual information Develop their problem-solving skills Enhance their academic writing proficiency Refine their data analysis techniques Save time and handle workload efficiently	Students use GenAI to deepen their understanding Save time: Students increase understanding of programming through quick ready-made code solutions and explanations	"If you don't understand something, you can just put it into ChatGPT and it explains it more clearly." "It just gives me a solution right away and explains the code to me which actually helps me in another way to learn."
GenAI challenges the objectives of learning Students' descriptions of using GenAI in education in ways they perceive as preparing them for future labor market tasks and employer expectations	Students use GenAI to perform tasks efficiently, reflecting expectations of speed and productivity in future workplaces	Students use GenAI to experiment with prompt engineering across tasks in design and product development, to develop interaction skills and save time	"It's great at filtering out exactly what you're looking for and summarizing it well [in tasks related to design and project work]. You'll use it for almost everything at work […] There's often time to be saved, and you can apply it to anything you feel you need it for. I don't think employers would mind; it's just another skill, like being good at programming or math. In the workplace, what really matters is how efficiently you can get the job done."

Theme	Semantic code clusters	Examples of semantic codes within clusters	Quote examples
	Students use GenAI as an assistant to solve tasks they consider relevant to future professional practice	Students use GenAI to produce and analyze text, including reports	"I could end up in a situation in the future where I need to write a summary of a comprehensive plan that I've created. If I then can use AI to generate the text, that might be the way I'll have to work in the future."
GenAI change the role of teachers Students' accounts of using GenAI instead of interacting with teachers, or in ways that affect teachers' work	Students use GenAI to obtain immediate and timely answers, instead of asking teachers or attending lectures	Students use GenAI to understand factual content instead of asking Teacher Assistants (TA)	"Sometimes I have questions for TA, but now I can just ask the questions to ChatGPT instead"
	Students circumvent teachers' rules by using GenAI in undetectable ways	Students use GenAI in a way that is difficult for teachers to detect	"People use it [GenAI] no matter what, because teachers basically can't detect it."
GenAI challenges the ethics of cheating Students' descriptions of how GenAI is used in ways they perceive as acceptable or unacceptable	Unacceptable GenAI use	Copy-pasting or letting GenAI generate content without verifying or engaging with the material is unacceptable	"Just copying and pasting from ChatGPT is basically cheating."
	Acceptable GenAI use	It is acceptable if GenAI supports students' own thinking and learning, rather than replacing it	"It's okay to use ChatGPT to structure a text, but you need to write it yourself."

Appendix 2: Overview of themes, semantic code clusters, and semantic codes of genai use across educational tasks

Theme	Semantic code cluster	Semantic codes of GenAI use across educational tasks
Selfdirected learning	Enhancing their academic writing proficiency	Using GenAI to support academic writing tasks, including improving style and grammar, structuring texts, creating essay outlines, translating drafts, and revising for clarity and tone
	Deepening their understanding of concepts and factual information	Asking GenAI to explain theoretical concepts, equations, and terminology Interpret lecture slides and course materials Translate academic texts to improve comprehension Retrieving and summarizing information from articles and PDFs
	Developing their problem-solving skills	Asking for step-by-step explanations of problem-solving processes, equations, or programming tasks Interpreting images and illustrations in assignments Verifying concepts and methods Using GenAI to explore and develop solutions to challenges, including reasoning through problems and enhance idea generation
	Refining their data analysis techniques	Asking GenAI to explain statistical methods and outputs Interpreting large datasets Understanding error messages in code and debugging and optimizing algorithms
	Saving their time and handling workload efficiently	Rapid data processing Extracting keywords from PDFs to reduce reading time Summarizing long texts for quicker understanding Asking GenAI for quick factual answers Handling repetitive tasks and routine tasks to GenAI to save time Increase understanding of programming through quick ready-made code solutions and explanations
GenAI challenges the objectives of learning	Training to perform tasks at high speed, which is expected to be important in future workplaces	Training with GenAI to quickly analyze large datasets Using GenAI to rapidly analyze text and produce reports Using GenAI to search for information quickly Using GenAI to construct technical solutions in shorter timeframes Coding quickly with the support of GenAI's ready-made solutions Using GenAI to experiment with prompt engineering across tasks in design and product development, to develop interaction skills and save time
	Training to use GenAI as an assistant to carry out tasks they expect to be relevant in future professional contexts	Using GenAI to assist in coding, data analysis, and problem-solving tasks. Using GenAI to produce and refine professionally worded written content, including emails, reports, and essays, while ensuring an authentic and appropriate tone
GenAI changes the role of teachers	Using GenAI to get immediate and timely answers instead of asking teachers or attending lectures	Using GenAI to obtain immediate and timely explanations of course content, including programming, mathematics, and theory-related concepts in societal planning and architecture, as an alternative to asking teachers or attending lectures Using GenAI to interpret and understand lecture slides and course materials, including technical examples and academic texts in programming, architecture, and societal planning, both as a complement to and substitute for teachers' lectures
	Using GenAI in ways that are difficult for teachers to detect	Modifying GenAI-generated essay content to align with academic expectations and reduce detectability Using GenAI to generate content for essays and project assignments, regardless of institutional restrictions, if they believe it's hard for teachers to detect

Theme	Semantic code cluster	Semantic codes of GenAI use across educational tasks
GenAI challenges the ethics of cheating	Unacceptable GenAI use	Using GenAI to produce written or technical content without understanding, including essays, reports, thesis sections, take-home exams, lab reports, and programming tasks. Students copy-paste or let GenAI generate content without verifying or engaging with the material, sometimes rewriting it to avoid detection Using GenAI to perform tasks such as graph creation, statistical interpretation, or risk analysis in data-driven assignments, if students bypass their own critical thinking and interpretation Using GenAI unfairly in group work or design projects, including written contributions or visualizations, if some students rely on GenAI while others contribute manually or invest significant effort, leading to imbalance and frustration
	Acceptable GenAI use	Note: Acceptable use has been interpreted as student accounts of GenAI use that are not described as problematic. This includes all tasks presented in the previous categories of the table, where GenAI is used to support students rather than replace their own efforts For example: Using GenAI to support their own thinking and learning, including tasks such as idea generation, summarizing information from articles, or structuring written assignments, in ways where students use GenAI as a tool to think in new ways and reflect on the content of their tasks Using GenAI to assist with technical tasks, such as quick ready-made code solutions or creating templates for data analysis, in a manner where students verify and understand the output Using GenAI transparently in collaborative work, including generating initial drafts or structures, as long as all group members agree and the use is clearly reported

Funding Open access funding provided by Chalmers University of Technology.

Declarations

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

Ethical approval All procedures in the study were conducted in accordance with applicable laws and institutional guidelines for research ethics ensuring strict adherence to ethical principles throughout this study. Detailed information about the study was provided to participants before beginning the data collection, reassuring them of their right to voluntary participation and withdrawal, and all participants provided their informed consent.

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Tiina Leino Lindell Tiina Leino Lindell explores how digitalisation, including the rapid emergence of AI, reshapes learning practices and the conditions of teaching across all levels of education. Her research investigates how students engage with and appropriate digital tools, and how the education profession responds to the pedagogical, organisational and ethical challenges that accompany digital transformation. By examining these shifting practices and responsibilities, her work seeks to generate insights that support the development of resilient and sustainable approaches for meeting both current and future educational needs.

Christian Stöhr Prof. Christian Stöhr leads the Digital Learning and Teaching research theme within the Department of Communication and Learning in Science at Chalmers University of Technology, Gothenburg, Sweden. His research focuses on the role of technology in engineering education with a particular interest in AI in education, flipped and hybrid pedagogies, and Massive Open Online Courses (MOOCs).