Generative AI Use and Academic Belonging in Computer Science Education: A Mixed-Methods Study

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Abstract

Generative AI tools have become increasingly prevalent in higher education, yet their psychological and social consequences for students remain under-explored. This study examines how generative AI use shapes computer science students' academic sense of belonging and perceived legitimacy, focusing on the LIACS community at Leiden University. A mixed-methods design was employed, combining a quantitative survey measuring perceived competence, impostor-type feelings, and academic belonging with in-depth qualitative interviews conducted with four computer science students at varying stages of their degree.

Neither measure of AI use was related to perceived competence, impostor-type feelings, or academic belonging in the survey data, though the direction of the relationships was consistently negative across every comparison. Significant gender differences were observed across all three psychological constructs, with female students reporting higher impostor-type feelings, lower perceived competence, and lower academic belonging than their male counterparts, whilst no comparable gender differences were found in AI usage patterns.

The qualitative data suggested that perceived dependence, rather than frequency of use, may be the more psychologically consequential variable. Students who experienced AI as substituting for their own thinking reported erosion in problem-solving confidence and heightened impostor feelings, whilst those who maintained cognitive ownership over their work reported no comparable costs.

The study concludes that generative AI use does not straightforwardly undermine belonging, but appears to interact with belonging patterns that were already uneven, making belonging more precarious for some students than others depending on the meaning they assign to their use and the position they occupy within the discipline.

Contents

1 Introduction

Generative Artificial Intelligence (AI) tools such as ChatGPT and GitHub Copilot have become deeply embedded in the daily practices of Computer Science (CS) students. Within a remarkably short period, these tools have moved from novelty to being near universally used in higher education, reshaping how students approach programming assignments, debug code, and prepare for examinations. Yet, while the technical evolution of these capabilities has attracted substantial academic interest, the psychological implications for the students who rely on them remain poorly understood.

At the same time, a well-established body of educational research has documented that a sense of academic belonging in Computer Science is fragile, unequally distributed, and deeply tied to a student's perception of competence and legitimacy within the discipline [3]. Students who doubt whether they truly belong, a vulnerability often heightened among women and under-represented demographics, face a greater risk of reduced motivation, a sense of isolation, and academic dropout. Central to this experience is the emotional strain of the impostor phenomenon, where individuals routinely attribute their academic milestones to luck or external factors rather than genuine ability [10].

What remains largely unexplored is how the rapid integration of generative tools into computing education interacts with these pre-existing psychological dynamics. When students solve complex programming problems primarily via automated assistance, the interaction may alter their internal benchmarks of learning ownership and technical fluency. Furthermore, if reliance on algorithmic support inadvertently replaces the collaborative peer interactions through which community is traditionally built, it may increase feelings of isolation and accelerate physical withdrawal from the campus environment. These issues sit at the intersection of distinct research lines, and now that generative tools are a normal part of studying computer science, they are worth taking seriously together.

This study investigates the relationship between generative AI use and the academic sense of belonging among Computer Science students at Leiden University, with particular attention to the roles of self-reported competence and impostor-type feelings in that relationship. The study explores whether and how these psychological constructs connect to patterns of AI use, and what that might mean for students' sense of legitimacy within the discipline. Using an explanatory sequential mixed-methods design [12], a quantitative survey was first deployed to map broader usage patterns and these proposed psychological links, followed by qualitative semi-structured interviews to explore how individual students experience these dynamics in their own words.

This research was conducted as a Bachelor's thesis at the Leiden Institute of Advanced Computer Science (LIACS), Leiden University, under the supervision of Anna van der Meulen and Tyron Offerman.

The study is guided by the following research questions:

RQ: How does generative AI use shape Computer Science students' academic sense of belonging and perceived legitimacy within their field?

SQ1: Which generative AI tools do Computer Science students use, how frequently do they use them, and in what learning contexts?

SQ2: How does the frequency of and perceived dependence on generative AI relate to students' impostor-type feelings and self-reported competence?

SQ3: How do students perceive the impact of AI use on the development of competencies such as debugging strategy, collaborative problem-solving, coding fluency, and technical communication?

The remainder of this thesis is structured as follows. Section 2 reviews the relevant literature regarding academic belonging in Computer Science education, the psychological frameworks of impostor syndrome, and the current state of generative AI integration in higher education. Section 3 describes the explanatory sequential mixed-methods research design, data collection instruments, and analysis procedures. Section 4 presents the quantitative results alongside the qualitative thematic findings. Section 5 discusses these findings in relation to the established theoretical framework and existing literature, as well as discussing the limitations of this study, and Section 6 concludes the study, proposing practical implications and directions for future research.

2 Related Work

2.1 Belonging in Higher Education and Computer Science

Sense of belonging is widely recognised as a fundamental psychological need, broadly defined as the perception of being accepted, valued, and included within a given social environment [3]. In higher education, belonging has been consistently linked to academic motivation, persistence, and student well-being. Belonging is not a static trait but a dynamic perception, continuously shaped by social interactions, institutional structures, and personal experiences.

A widely used theoretical framework to understand belonging is Self Determination Theory (SDT), which identifies three basic psychological needs, namely relatedness, competence, and autonomy, whose fulfilment underlies sustained motivation and well-being [23]. SDT posits that when these needs are met within educational environments, students are more likely to be intrinsically motivated, engaging in learning for its inherent value rather than out of external pressure. Conversely, experiences of exclusion or perceived incompetence can erode students' motivation, well-being, and sense of belonging.

Relatedness, in particular, concerns the need for meaningful social connections and a sense of belonging within one's learning community; it is facilitated by experiences of respect and care, and undermined by experiences of exclusion or disconnection [24]. The need for competence, meanwhile, concerns the feeling of mastery and the sense that one can succeed and grow; it is most effectively supported through well structured environments that offer appropriate challenge, positive feedback, and opportunities for development [24]. Together, these two needs provide the theoretical foundation for understanding how disruptions to self-evaluation and social connection can undermine a student's sense of place within their academic discipline.

Belonging is thus a central concern in higher education broadly, shaped by the degree to which students feel competent, connected, and able to act autonomously within their learning environment. In Computer Science, technical competence may function as a marker of legitimate membership in a way that few other disciplines replicate. Perlmutter et al. [19] examined belonging in post-secondary Computer Science education through a qualitative study of student-TA interactions across introductory, intermediate, and advanced courses. Drawing on SDT, their analysis found that belonging in Computer Science is deeply tied to students' perceptions of competence, recognition, and legitimacy within the discipline. Beyond the three SDT needs, they identified safety and access as additional components of Computer Science belonging specifically: safety referring to students' ability to ask questions and make mistakes without fear of judgment or ridicule, and access referring to the practical and social conditions that enable meaningful participation in the Computer Science community, such as access to support, resources, and networks of peers. Student-TA interactions, particularly during office hours, played a significant role in shaping whether students felt accepted as legitimate members of that community.

Perlmutter et al.'s [19] findings point to a broader pattern: belonging in Computer Science is not merely a function of academic performance, but is actively constructed through social and institutional signals about who is recognised as a legitimate member of the field. This construction is not uniform across student populations. Research in STEM more broadly has shown that gender and representation play a significant role in shaping belonging: Rainey et al. [22] found, in interviews with over 200 students across STEM disciplines, that white men reported the highest levels of belonging, whereas women of colour reported the least. Notably, representation within one's specific subdiscipline appeared to independently shape women's sense of belonging, suggesting that the more male-dominated a field, the more precarious belonging becomes for women within it.

This pattern is particularly acute in CS, one of the most male-dominated disciplines within STEM. Women in Computer Science face persistent belonging uncertainty shaped not only by numerical under-representation, but also by the cultural identity of the field itself [30]. Cheryan et al. [8] demonstrated that the cultural stereotypes surrounding computer science, portraying it as solitary, male-oriented, and requiring innate brilliance, actively reduce women's sense of belonging and interest in the field, even when their academic performance is equivalent to that of their male peers. Widdicks et al. [30] conducted focus groups with women in a university Computer Science department and found that their experiences of belonging were shaped not only by academic performance but by persistent feelings of being out of place in a discipline whose culture they did not see themselves reflected in. Wu et al. [31] similarly found that Women-in-Computing groups served as an important mechanism for belonging and academic identity formation, suggesting that women in Computer Science actively seek out spaces where their legitimacy is affirmed rather than assumed. These studies indicate that belonging is unevenly distributed along gender lines, and that this unevenness is especially pronounced in disciplines like Computer Science where the dominant culture remains strongly male-coded.

2.2 Impostor Syndrome as a Mechanism Undermining Belonging

A concrete psychological mechanism through which belonging in Computer Science can be undermined is impostor syndrome, defined as the internalised belief that one's success is undeserved and that one risks being exposed as incompetent despite objective evidence to the contrary. Although the phenomenon was originally described in the context of high-achieving women [10] , Price et al. [21] have since shown it to be widespread across academic fields and genders. A meta-analysis of 115 effect sizes involving more than 42.000 participants found that women consistently score higher on measures of impostor phenomenon than men, with a small to moderate but highly consistent effect across disciplines and time periods. Importantly, the magnitude of this gender difference varied by disciplinary context, with larger differences observed in academic settings than in business environments, suggesting that the nature of the field shapes how impostor feelings are distributed along gender lines.

Within computer science specifically, these broader patterns take on particular significance. Chen et al. [7] investigated impostor syndrome among final-year Bachelor's degree Computer Science students using a combination of pre- and post-questionnaires, eye-tracking, and biometric measurements. Their findings revealed that students with higher levels of impostor feelings spent more time on programming tasks and were less likely to solve them correctly, suggesting that impostor syndrome not only reflects negative self-perception but actively interferes with performance. The study further found that male-identified students reported significantly lower levels of impostor syndrome than their peers, mirroring the broader gender differences identified by Price et al. [21] and reinforcing the pattern of belonging uncertainty among women in Computer Science discussed in the previous section. Women in Computer Science thus face a compounded challenge: structural and cultural factors make belonging uncertainty more likely, while the self-evaluative mechanisms of impostor syndrome further erode it.

Although impostor syndrome is predominantly associated with negative outcomes, recent work suggests that the phenomenon is more nuanced than a purely deficit-based perspective implies. Tewfik et al. [27] argue that individuals experiencing impostor-like feelings may become more attuned to others, and therefore interpersonally more sensitive, which can in some social contexts lead to positive outcomes. While this does not negate the substantial evidence linking impostor syndrome to reduced well-being and academic performance, it does indicate that its effects are context-dependent and shaped by the broader environment in which students operate.

Together, the literature on belonging and impostor syndrome in Computer Science establishes a clear link: students' sense of legitimacy within the discipline is closely tied to self-perceived competence, and disruptions to that self-evaluation can meaningfully undermine their sense of place in the field. For women in Computer Science, this dynamic is particularly pronounced. Given that both belonging and self-evaluation are sensitive to the social and technological conditions of the learning environment, the rapid integration of generative AI into Computer Science education raises important questions about how these mechanisms may be further shaped or disrupted.

2.3 Generative AI in Computer Science Education and Student Well-being

The emergence of generative AI tools such as ChatGPT, GitHub Copilot, and similar large language model-based applications has prompted substantial debate across higher education. This debate spans questions of academic integrity, pedagogical design, assessment reform, and the evolving relationship between students and their learning environments. At the policy level, universities worldwide have been confronted with the challenge of regulating generative AI use in ways that are both enforceable and educationally meaningful. A critical review of generative AI policies at 20 leading universities found that the primary concern represented in these policies is that students may not submit original work, with generative AI frequently framed as external assistance that undermines independent intellectual contribution [18]. Yet how students actually engage with generative AI is considerably more nuanced than this framing implies. Cabrera et al. [6] found that while generative AI tools are widely used among university students, fewer than 25 percent regard their outputs as reliable, and awareness of institutional guidelines remains strikingly low, with many students uncertain about what is and is not permitted in their coursework. The result is an environment in which students navigate generative AI use under conditions of persistent uncertainty, navigating inconsistent expectations that vary not only between institutions but between individual courses and instructors [28].

Beyond effects on learning and self perception, research has also raised concerns about the implications of generative AI for students' social and emotional experiences. Crawford et al. [11] evaluated 387 university students and their relationship with AI tools using structural equation modelling. Their findings revealed a nuanced picture: while AI chatbot use was associated with short-term performance benefits, accounting for social support, psychological well-being, loneliness, and sense of belonging reversed this, with AI use showing an overall negative association with these outcomes. The study found evidence of a human-substitution effect: students who turned to AI for support in place of human interactions experienced poor social outcomes, including increased loneliness and reduced belonging. Al-Zahrani [1] similarly found that while students acknowledged functional benefits of AI chatbots, they also reported concerns about diminished human connection and emotional support. These outcomes map directly onto the SDT need for relatedness: when the peer relationships are eroded, students' sense of belonging is put at risk regardless of their academic performance.

Within this broader landscape, a growing body of empirical work has examined how students in Computer Science specifically engage with generative AI tools, and what effects this has on their learning and self-perception. Research [15, 25] on usage patterns has challenged early assumptions that students primarily use these tools to avoid intellectual effort, finding instead that usage is varied: students employ generative AI for code explanation and debugging at least as often as for code generation, and many report perceived benefits for efficiency and problem-solving alongside recurring concerns about over-reliance and poor output quality.

However, a more concerning pattern emerges when examining the differential effects of generative AI use across student profiles. Amoozadeh et al. [2] found that in approximately one third of observed cases, CS1 students submitted tasks directly to a generative AI tool without independent effort, and few verified the outputs they received. More strikingly, Prather et al. [20] found a widening gap between students who struggled and those who did not: while stronger students were able to use generative AI to accelerate work they already understood, struggling students experienced compounded metacognitive difficulties and frequently finished tasks with an illusion of competence, believing they had performed better than they actually had. These findings are directly relevant to the belonging mechanisms discussed earlier: if generative AI use can distort students' self-evaluation of their own competence, it may also affect their perceived legitimacy within the discipline.

The effects of generative AI on students' self-perception are not, however, exclusively negative. While Prather et al. [20] demonstrated that AI use can distort self-evaluation among struggling students, other research suggests that the same group may also stand to benefit the most from AI support under different conditions [26]. Shao et al. [26] , in a quasi-experimental study with 200 STEM Bachelor's degree students, found that AI-assisted learning was associated with significantly higher intrinsic motivation and self-efficacy compared to traditional support, with this effect being more pronounced among lower-achieving students than higher-achieiving ones. Drawing on SDT, the authors argue that AI tools may enhance students' sense of competence and autonomy by providing personalised, low-pressure, real-time support. These are precisely the conditions under which the SDT needs for competence and relatedness are most likely to be met. This finding is further supported by Liang et al. [17] , who found in a survey of 389 participants that interaction with AI tools positively correlated with learning outcomes, mediated by increases in self-efficacy and cognitive engagement. These studies suggest that the effects of AI on students' self-perception are not uniformly negative, but depend significantly on how the tools are used and in what context.

2.4 Identifying the Gap

The bodies of literature reviewed above converge on a shared blind spot. Research on belonging and impostor syndrome in Computer Science has established that students' sense of legitimacy is closely tied to self-perceived competence, shaped by social interactions, performance feedback, and identity-related signals [19, 7]. Research on generative AI in Computer Science education has demonstrated that these tools are widely used, that their effects are uneven, and that they can distort students' self-evaluation, particularly among those who already struggle [20, 2]. Research on AI and student well-being has raised concerns about loneliness and the psychological costs of reduced human interaction [11]. Yet these three lines of inquiry remain largely disconnected: belonging research does not consider the role generative AI might play, and generative AI research rarely examines psychological or identity-related outcomes. This disconnection is particularly notable given the conditions under which students currently use generative AI: in an environment characterised by widespread uncertainty around AI policies, students are left to navigate these tools without clear institutional guidance, and without an understanding of how their use might be shaping their sense of who they are as members of a Computer Science community. No study to date has directly investigated whether and how patterns of generative AI use relate to Computer Science students' academic sense of belonging and perceived legitimacy, particularly in a Dutch, discipline-specific context. The present study aims to address that gap.

3 Approach

This chapter describes how the study was carried out. Section 3.1 outlines the explanatory sequential mixed-methods design and how the quantitative and qualitative phases were intended to be integrated. Section 3.2 describes the participants recruited for the survey and interview phases. Section 3.3 describes the survey and interview instruments used to collect data, and Section 3.4 describes how data collection was carried out for both phases. Finally, Section 3.5 describes the quantitative and qualitative analysis procedures applied to the resulting data.

3.1 Research Design

This study employed an explanatory sequential mixed-methods design [12], consisting of two phases that were largely sequential. In the first phase, a quantitative survey was administered to Computer Science students at Leiden University. Recruitment for the interview phase began during the survey distribution period, as participants were invited to indicate their willingness to be interviewed at the end of the survey. The two phases were largely sequential but partially overlapping (see Section 3.4.2). The interview guide was developed prior to the survey distribution and remained consistent throughout the data collection period, ensuring that all participants were asked about the same themes regardless of when their interview took place.

This design was chosen because it allows for the identification of broad patterns across a larger sample, while also enabling a deeper exploration of how individual students experience and interpret those patterns. Quantitative data alone would not capture the nuanced, identity-related processes central to this study's research question, while qualitative data alone would not allow for the identification of systematic relationships between generative AI use and academic belonging. The combination of both methods therefore directly serves the study's aim of understanding not only whether a relationship exists between generative AI use and belonging, but also how and why that relationship manifests in students' lived experiences.

In line with this explanatory sequential design, the quantitative and qualitative datasets were intended to be integrated at the level of interpretation rather than data collection. The survey was designed to establish descriptive patterns and identify relationships across the sample, whilst the interviews were intended to provide the contextual depth necessary to explain, elaborate, and in some cases complicate those patterns, regardless of whether a given survey result reached statistical significance. This integration was expected to work in two main ways. First, the interview data would help interpret and add nuance to the patterns identified in the survey, whether by helping explain a finding, by illustrating what a quantitative pattern might mean for individual students, or by complicating a pattern that initially looked straightforward. Second, the interviews were expected to raise questions the quantitative instrument was not designed to address, such as the subjective meaning students assign to their AI use, which could then be considered alongside the broader quantitative patterns to build a more complete picture.

3.2 Participants

3.2.1 Survey

The survey was administered to students enrolled in a Computer Science or CS-related (LIACS) Bachelor's or Master's programme at Leiden University, specifically BSc Computer Science, BSc Data Science and Artificial Intelligence, BSc Informatica en Economie, BSc Bioinformatics, and MSc Computer Science. These programmes were selected because they all require programming as a core component of the curriculum, making their students directly relevant to the research question. No other inclusion criteria were applied; all students enrolled in one of these programmes were eligible to participate regardless of their year of study, prior experience, or level of generative AI use.

No formal minimum response threshold was set in advance, though a target of approximately 40 responses was used as an informal benchmark during the data collection period. Given the voluntary nature of participation and the practical constraints of recruiting within a limited timeframe, this number was considered sufficient for exploratory quantitative analysis.

3.2.2 Interviews

Four semi-structured interviews were conducted with Computer Science students at Leiden University. Interview participants were primarily recruited using a nested approach through the survey phase, where respondents were invited to provide their contact details to volunteer for a follow-up session. However, to mitigate an initial all-male demographic imbalance and deliberately seek a more diverse perspective, purposive sampling was subsequently employed. Specifically, one participant, a female-identified student, was approached directly and invited to participate based on her programme enrolment. This combined strategy allowed the qualitative phase to capture a wider range of localised student experiences within the programme.

The final sample consisted of three male-identified students, and one female-identified student, split between two Bachelor's students in their final year, and two Master's students. Interviews lasted approximately 48 minutes on average, which is slightly longer than initially anticipated.

Given the small sample size ($N = 4$), the qualitative cohort is inherently restrictive and heavily skewed toward male-identified experiences. Crucially, none of these individual accounts, neither the single female voice nor the three male voices, can be taken as statistically representative of the broader, systemic experiences of the LIACS community as a whole. The goal of these interviews is not to generalise findings across the whole programme. Instead, this small sample is used to look deeply at four distinct individual experiences, offering comprehensive case accounts that help explain how different types of students experience academic pressure, belonging, and AI use.

3.3 Instruments

3.3.1 Survey

The survey consisted of six sections. Section A collected demographic information, including age range, gender identity, international student status, programme, year of study, prior programming experience, optional information on functional impairments, and whether they use generative AI in their studies to begin with. Sections C through F measured the core constructs of interest using five-point Likert scales ranging from 1 (Strongly disagree) to 5 (Strongly agree), whereas Section B used a frequency scale ranging from 1 (Never) to 5 (Always).

Section B measured generative AI use through six items assessing the frequency and nature of students' AI usage in the context of their studies, distinguishing between a passive measure, which captures general frequency of use and reliance on AI when stuck, and an active measure, which captures specific behaviours such as requesting complete solutions, debugging with AI, and discussing AI-generated code with peers. In this section, participants also got a field to add any remarks regarding their generative AI use, should they have felt the need to. Section C measured perceived competence using five items based on the competence subscale of Self-Determination Theory [23], assessing students' confidence in their programming abilities and their capacity to meet the demands of their programme. Section E measured perceived AI impact on programming-related skills through five items developed for this study, assessing whether AI use was perceived to affect students' ability to debug independently, collaborate with peers, and communicate technical ideas.

Section D measured impostor-type feelings using eight items adapted from the Clance Impostor Phenomenon Scale [9]. In this section too, participants got a field to add any remarks regarding their generative AI use, should they have felt the need to. The CIPS was originally developed to measure the impostor phenomenon as a multidimensional construct, capturing the various ways in which individuals may doubt the legitimacy of their own achievements. The adapted items cover seven distinct constructs. Fear of exposure refers to the concern that others will discover one is less competent than perceived, which is especially important in Computer Science where technical competence is highly visible and frequently evaluated through code reviews, presentations, and collaborative work. Luck attribution captures the tendency to attribute success to external factors such as timing or chance rather than to one's own ability, which may be especially salient when students rely on AI to complete tasks they could not have completed independently. Fraudulence feeling refers to the sense of having worked one's way to a current level without truly earning it, which connects directly to questions of legitimacy and belonging within the discipline. Discounting success describes the tendency to downplay achievements as undeserved, while external attribution captures the related pattern of attributing positive feedback to the evaluator's kindness rather than to one's own merit. Failure to internalise success refers to the persistent difficulty of accepting that one's achievements are genuinely earned, even in the face of repeated success. Finally, comparative inadequacy captures the feeling of being less naturally capable than peers, even when objective performance is similar. This is a construct that is directly relevant in Computer Science education, where students frequently compare their abilities and pace of learning to those of their classmates.

Section F measured academic belonging using nine items adapted from the Psychological Sense of School Membership scale [13]. In this section too, participants got a field to add any remarks regarding their generative AI use, should they have felt the need to. The PSSM was originally developed to measure students' sense of belonging within a school environment across four core constructs. Membership refers to the feeling of being a real and legitimate part of the community, captured in this study through items such as *"I feel like a real part of the Computer Science community at this university"*, adapted from the original *"I feel like a real part of this school."* Recognition concerns the degree to which peers and instructors acknowledge and respect a student's contributions, which in a Computer Science context is closely tied to the visibility of one's technical work. Social belonging captures the quality of interpersonal relationships within the programme, reflecting whether students experience their peers as friendly and supportive. Comfort and psychological safety concern students' ability to ask for help, make mistakes, and be themselves without fear of judgment. These are constructs that align closely with the safety component identified by [19] as a key dimension of belonging in Computer Science specifically. Acceptance refers to the feeling of being welcomed and included by fellow students, while the broader sense of belonging captures whether students feel they genuinely fit within the programme as a whole. Finally, perceived value reflects students' sense that their presence matters within the learning environment, adapted from the PSSM concept of feeling important within one's community.

Across sections B, D, and F, optional open-ended text fields were included following the closed Likert-scale items. Whilst the standardised scales used in this study are well-validated instruments, they are necessarily fixed in their framing and limited in the range of experience they can capture. This matters especially for constructs as personal and context-dependent as these. A student who uses AI exclusively as a last resort after exhausting all other options, for instance, may select the same frequency response as one who reaches for it immediately, yet their experiences and the psychological consequences of that use may differ considerably. Similarly, a student whose sense of not belonging stems from identity-related factors rather than academic performance may find that no single scale item adequately captures their situation. The open-ended fields were therefore included to give participants the opportunity to contextualise, qualify, or expand upon their responses where they felt the closed items were insufficient.

Where existing scales were used, item wording was adapted to reflect the Computer Science learning context while preserving the underlying constructs. For the CIPS, items were reworded to refer explicitly to CS-specific situations, such as programming tasks, code reviews, and performance within the Computer Science programme, rather than academic achievement in general. For the PSSM, items were adapted to reflect belonging within a Computer Science programme and community specifically, rather than a school environment more broadly. One example of an adapted PSSM item is *"I feel like a real part of the Computer Science community at this university"*, which was adapted from the original item *"I feel like a real part of this school."* The competence items in Section C were developed in line with SDT's definition of competence as the sense of mastery and the belief that one can succeed and grow within a given environment [23]. The full survey is included in Appendix A.

3.3.2 Interview Guide

Semi-structured interviews were conducted using an interview guide developed specifically for this study. All interviews were conducted in English to ensure accessibility for both domestic and international students within the target population. Interviews took place either online via Microsoft Teams or in person on the university campus, depending on the participant's preference.

The guide consisted of three thematic blocks: generative AI use, self-perception and dependence, and belonging and legitimacy, preceded by a brief warm-up block on background and followed by a closing block. The blocks were ordered to move from concrete and relatively neutral topics towards more personal and potentially sensitive themes, in line with best practices for qualitative interviewing in sensitive research contexts [16].

Given the potentially sensitive nature of questions about belonging, impostor-type feelings, and self-perceived competence, particular care was taken in the design of the belonging and legitimacy block. This block was introduced with the following framing: *"We are now going to talk about how you feel as a student within your programme. I do not only mean academically, but also how you experience your place within it. Maybe you need some time to think about certain questions, but try to say what comes into your mind when it does."* This introduction was intended to broaden participants' frame of reference beyond academic performance, while also signalling that there was space to reflect and that no particular answer was expected. Questions within this block were sequenced to first explore students' general sense of belonging independently, before introducing the connection to AI use. This ordering was intended to allow participants to reflect on their belonging experiences without being primed to attribute them to AI, reducing the risk of leading responses on a topic central to the study's research question.

Transition sentences were used throughout the guide to link topics explicitly to what the participant had previously shared, ensuring that the interview felt conversational rather than formulaic. An example of such a transition is: *"You mentioned that [assessment of own programming skills]. I am curious whether your [non] use of AI also plays a role in that."*

A key example of a question that directly connects the two central constructs of the study is taken from the belonging and legitimacy block: *"If you can only solve a problem with the help of AI, what does that do to how you feel about yourself as a Computer Science student?"* This question was deliberately formulated to be open-ended, avoiding assumptions about whether the effect would be positive or negative, while directly probing the relationship between AI-assisted problem-solving and students' sense of legitimacy within the discipline. It was typically asked after participants had already reflected on both their AI use and their general sense of belonging, ensuring sufficient context for a meaningful response.

Prior to data collection, a pilot interview was conducted with an individual from the researcher's personal environment to test the flow and timing of the guide and to practise recording and note-taking procedures. The pilot confirmed that the guide could be completed within the estimated 30 to 45 minutes and that the ordering of topics felt natural and manageable for the participant. Neutral phrasing was used throughout to avoid leading participants towards particular responses, for example using *"How does that feel for you?"* rather than *"Don't you find that difficult?"* The full interview guide is included in Appendix B.

3.4 Procedure

3.4.1 Survey

Prior to distribution, the survey was piloted with a small group of individuals from the researcher's personal environment, including one Computer Science student and a couple of participants from outside the field. Participants were asked to complete the survey and provide feedback on the clarity of the instructions, the comprehensibility of individual items, and the overall flow. This approach allowed for feedback both from someone familiar with the Computer Science context and from individuals who could identify ambiguous or overly technical phrasing that might affect comprehension more broadly. The pilot confirmed that the survey could be completed within the estimated 12 minutes and resulted in minor adjustments to item wording for clarity.

Following this pilot, a digital quantitative survey was distributed over a four-week period throughout May 2026, hosted on the university-approved platform Qualtrics. The survey was distributed through student Discord servers and WhatsApp groups. These channels were chosen because they are perceived by the researcher to be widely used by LIACS students at Leiden University for informal communication and are therefore likely to reach a broad cross-section of the target population.

Prior to accessing the survey items, participants were presented with an integrated informed consent page. This page detailed the study's aims, the voluntary nature of participation, the right to withdraw at any point without penalty, and the anonymisation of all survey responses. Participants were required to actively check a consent box before the survey would proceed.

Upon completing the survey, participants were invited via a final page to volunteer for the subsequent qualitative interview phase. To preserve the anonymity of the primary survey data, the collection of contact details was never done at the same time the collection of the survey data, ensuring that no survey response profile could be connected to an individual identity.

A reminder message for the survey was sent through the same recruitment channels approximately one week after initial distribution, followed by a second and final reminder approximately ten days later, in order to maximise response rates.

3.4.2 Interviews

The qualitative phase began in mid-May 2026, overlapping partially with the quantitative phase. This overlap was a pragmatic decision to optimise data collection within the available time frame. Recruitment for the interview phase began concurrently with the survey distribution, as participation was solicited mainly through the final page of the survey itself. All four interviews were conducted before the formal closure of the survey window. Because the semi-structured interview guide had been developed and piloted prior to data collection, its structure and content remained consistent across all interviews, regardless of when they took place.

Prior to commencing data collection, a pilot interview was conducted with an individual from outside the target sample to evaluate the clarity and timing of the interview guide. The pilot confirmed that the sessions would fall within the anticipated 30- to 45-minute time frame and demonstrated that the questions were clearly understood, requiring no structural modifications before formal interviewing began.

Then, participants who volunteered their contact details were contacted via email to schedule the session. All interviews were conducted in English and took place either in a reserved private room at Leiden University, or via a secure Microsoft Teams video call, depending on the participant's stated preference. Prior to the start of each recording, the researcher verbally re-established the conditions of participation and presented participants with a written informed consent form confirming their agreement to audio recording and the subsequent use of anonymised transcripts.

Each interview was recorded using two independent digital audio devices to safeguard against technical failure. Immediately following each session, the audio files were transferred to an encrypted cloud storage drive, and the local copies were permanently deleted from the recording devices.

Transcription was carried out by the researcher. During this process, all identifiable information, including names, specific course titles, project names, instructor references, and explicit demographic disclosures, was removed and replaced with generalised placeholders (e.g., [name of subject]). Each participant was assigned a standard alphanumeric pseudonym (P1 through P4) to ensure consistent anonymisation across all subsequent analysis and reporting.

3.5 Data Analysis

3.5.1 Quantitative analysis

Quantitative data collected through the survey was analysed using a custom Python script, employing the pandas, scipy, and pingouin libraries. The analysis proceeded in three sequential stages: scale validation, bivariate correlation, and group comparison.

Prior to any inferential analysis, the internal consistency of the three composite scales was assessed using Cronbach's alpha(α), applied to the Perceived Competence items ($Q15$–$Q19$), the Impostor-type Feelings items ($Q20$–$Q27$), and the Academic Belonging items ($Q33$–$Q41$). This step was necessary to verify that the individual Likert-scale items within each block reliably measured the same underlying psychological construct before being collapsed into a single mean score for further analysis. Only scales demonstrating acceptable internal consistency ($\alpha \geq .70$) were retained in their composite form.

Bivariate relationships between the AI usage sub-scales (*ai_passive*, *ai_active*), which describe active AI usage and a feeling of reliance on AI respectively, and the three composite psychological scores were examined using Spearman's rank-order correlation (ρ). Spearman's correlation was selected over Pearson's for three methodological reasons. First, the survey items use ordinal Likert scales, which means the interval distances between response options cannot be assumed to be equal. Second, the composite scores were not normally distributed. Third, Spearman's correlation is robust under small sample sizes, making it the appropriate choice for a sample of this scale. Rather than comparing raw values, Spearman's ρ evaluates the relative ranks of observations, asking whether students who rank higher on AI use also tend to rank higher or lower on impostor syndrome, belonging, or competence. Statistical significance was assessed at $p < .05$.

Group differences were examined using two non-parametric tests. To compare scores between male and female participants, the Mann-Whitney U test was applied. This test was chosen as the non-parametric equivalent of an independent samples t-test, appropriate given the ordinal nature of the data, the absence of normal distribution, and the unequal group sizes between genders. To examine whether scores differed across academic years (Year 1, Year 2(+), and Year 3+), the Kruskal-Wallis test was applied as the non-parametric equivalent of a one-way ANOVA, suitable for comparing three or more independent groups on ordinal data with small and unequal sample sizes.

For the open-ended text entry fields within the survey, a simple analysis approach was used compared to the full qualitative analysis used for the interviews 3.5.2. Because these text boxes only provided short answers, they did not require a complex thematic analysis. Instead, the responses were read through, filtered for relevance, and sorted into a few basic topic categories. This was done purely to help explain and add context to the patterns found in the numerical data. A more detailed and formal thematic analysis was reserved for the full interview transcripts.

3.5.2 Qualitative analysis

The qualitative data from the semi-structured interviews was analysed using Reflexive Thematic Analysis (RTA). This study uses the original six-phase framework by Braun and Clarke [4] because it gives a clear, step-by-step method for reading, coding, and sorting data. However, the analysis also follows their updated guidelines [5], which explain that coding and theme generation are subjective processes. Using both papers allows the study to follow a strict structural order while acknowledging that the researcher's perspective as a student plays a role in interpreting the text. This perspective was managed carefully to ensure personal assumptions about AI did not distort the participants' actual meanings.

The analysis followed these six phases:

- Familiarisation: The transcripts were read and re-read multiple times to get to know the data well, while noting down initial ideas about how students use AI, their emotional struggles, and their relationships with peers.

- Coding: Initial codes were created by targeting specific, meaningful segments of the text rather than coding every line sequentially. This step focused on the direct meaning of relevant statements, such as explicit mentions of tight deadlines, code errors, or university regulations.

- Generating Initial Themes: Codes from all four participants were grouped into clusters based on shared ideas. For example, individual codes like Deadline pressure (P1), Deadline-forced offloading (P3), and Compelled efficiency (P4) were grouped to build a broader theme about time pressures.

- Reviewing Themes: These initial themes were checked against the coded quotes and the full transcripts. This ensured that the quotes within a theme fit together well, and that each theme was distinct from the others.

- Defining and Naming Themes: The themes were turned into clear stories. The titles were adjusted to reflect broad concepts rather than simple topics, such as changing a topic like "Deadlines" into the theme AI Usage as a Response to Time and Institutional Pressures.

- Producing the Report: The final phase splits the work between the Results and Discussion chapters. The Results section describes the findings by weaving participant quotes together with the codes. This shows exactly how the data supports each theme without over-analysing the text. The deeper interpretation, which connects these findings to existing academic literature on student identity and ethics, is kept entirely for the Discussion section.

Table 1: Sample Distribution by Programme, Year, and Gender

Programme	Gender Year	Female	Male	Non-binary/Third gender	Total
BSc CS	BSc Year 2	2	2	0	4
	BSc Year 3+	3	9	1	13
BSc Data Science	BSc Year 2	0	1	0	1
	BSc Year 3+	0	2	0	2
MSc Computer Science	MSc Year 1	3	4	0	7
	MSc Year 2+	0	3	1	4
Total		8	21	2	31

4 Results

This chapter presents the findings of the study in two parts, corresponding to the two phases of the explanatory sequential design described in Section 3. Section 4.1 reports the quantitative survey results, including the psychometric properties of the composite scales, descriptive patterns in AI use and the three psychological constructs, the relationships between them, and group comparisons by gender and academic year. Section 4.2 then reports the findings of the semi-structured interviews, structured around five thematic patterns identified through inductive thematic analysis. Open-ended responses collected within the survey are reported alongside the relevant quantitative findings in Section 4.1, where they serve as illustrative additions to the closed-item data rather than as a separate analysis.

4.1 Survey

4.1.1 Sample and Demographics

A total of 31 valid participants formed the final sample upon which the quantitative results are based. This dataset was established following the programmatic removal of Qualtrics metadata rows, preview responses, and incomplete entries from the initial collection pool. Whilst 31 complete profiles were available for the generative AI usage scales, minor instances of item non-response occurred within specific survey subsections. Consequently, the total sample size varies slightly across individual sub-analyses, leaving 27 valid profiles available for the academic belonging scale.

Table 1 presents the distribution of participants across programme, year of study, and gender. The sample consisted predominantly of male students ($n = 21$), while eight participants identified as female and two identified as non-binary or a third gender.

Most respondents were enrolled in the Computer Science Bachelor's degree ($n = 17$), followed by the Computer Science Master's degree ($n = 11$) and the Data Science Bachelor's degree ($n = 3$). The largest subgroup within the sample consisted of Bachelor Computer Science students in their third year or later ($n = 13$). Overall, the sample included students from both Bachelor and Master programmes and represented multiple stages of academic progression.

4.1.2 Psychometric Reliability

Internal consistency for each question block was evaluated using Cronbach's alpha (α) prior to constructing composite scales. The Impostor-type Feelings scale and the Perceived Competence scale both demonstrated high reliability ($\alpha = .92$), while the Academic Belonging scale showed good internal consistency ($\alpha = .88$). Because all three values exceeded the standard acceptability threshold of $\alpha = .70$, the items within each block were aggregated into composite mean scores ranging from 1 to 5 for subsequent analysis. Higher composite scores represent a greater intensity of the measured construct: higher impostor-type feelings scores indicate stronger self-doubt, higher competence scores indicate greater confidence in programming abilities, and higher belonging scores indicate a stronger sense of membership within the programme.

The same procedure was applied to the five items measuring perceived AI impact on skills, after reverse-coding the two positively worded items (Q28, Q31) so that all five items pointed in a consistent direction alongside the three negatively worded ones (Q29, Q30, Q32). Here, however, the result was a negative alpha ($\alpha = -.43$), indicating that the five items do not measure a single underlying construct and should therefore not be combined into one composite score; they are instead reported as separate items in Section 4.1.3.

4.1.3 Descriptive Statistics

An overview of the central tendencies and distributions for the aggregated psychological scales and generative AI usage indexes is presented in Table 2. Overall, the sample showed high baseline levels of perceived competence ($M = 4.09$, $SD = 0.95$) and a relatively strong sense of academic belonging ($M = 3.66$, $SD = 0.79$). Self-reported impostor-type feelings were moderate across the cohort ($M = 2.53$, $SD = 1.09$).

Differences were observed between types of generative AI engagement. The composite mean score for the passive AI measure ($M = 2.88$, $SD = 1.26$) was higher than that of the active AI measure ($M = 2.03$, $SD = 0.70$). The passive AI measure scores covered the full range of the scale (Min = 1.00, Max = 5.00), whereas the active AI measure scores were more restricted, with no student in the sample scoring higher than 3.33.

Table 2: Descriptive Statistics for Composite Scales and AI Usage Indexes

Construct / Scale	N	Mean	Median	SD	Min	Max
Perceived Competence	28	4.09	4.40	0.95	1.60	5.00
Impostor-Type Feelings	27	2.53	2.75	1.09	1.00	4.25
Academic Belonging	27	3.66	3.89	0.79	1.78	4.78
Passive AI Use	30	2.88	2.75	1.26	1.00	5.00
Active AI Use	30	2.03	2.00	0.70	1.00	3.33

A descriptive analysis of the individual generative AI items was conducted to examine specific behaviours within the sample. Regarding the general frequency of use (Q9), 47% of respondents reported using generative AI for coding assignments frequently or always (response options 4 or 5), while 17% reported never using it. This distinction between general use and never using AI at all is corroborated by a direct screening item asked earlier in the survey, in which 19% of respondents indicated they did not use generative AI tools in their studies at all. The detailed usage items completed by this group were consistent with this self-report, with their scores on both the passive and active AI usage measures sitting close to the floor of each scale.

For complete solution generation (Q10), 50% of respondents reported never asking AI to generate a complete solution, while 13% reported doing so frequently. For debugging (Q11), usage frequencies were more distributed, with 33% reporting frequent use and 27% reporting never using AI for this purpose. The self-reported reliance on AI when stuck (Q12) showed a similar distribution, with 33% reporting frequent reliance and 20% reporting none. Finally, 53% of respondents reported never discussing AI-generated code with their peers (Q13), indicating that AI usage is a predominantly solitary practice within this sample.

A related set of items, in Section E of the survey, asked students how much they agreed that AI use had affected specific skills and habits, using a five-point scale ranging from 1 (Strongly disagree) to 5 (Strongly agree). As explained in Section 4.1.2, these five items did not form a single construct, so each is reported individually here rather than as a composite score. Table 3 presents the full distribution of responses across all five items. Responses were mixed for the two items concerning individual technical skill: for "AI has improved my ability to debug code independently" (Q28), responses leaned toward disagreement ($M = 2.22$, $SD = 1.19$), with 63% of respondents selecting "Strongly disagree" or "Somewhat disagree." A similarly mixed pattern was observed for "AI has helped me write more readable and maintainable code" (Q31, $M = 2.48$, $SD = 1.48$), where responses were spread fairly evenly across the scale rather than clustering toward agreement or disagreement.

Responses were more clearly directional for the items concerning collaboration and feedback-seeking. A majority of students agreed that AI use had reduced how much they solved problems together with peers (Q29, $M = 3.56$, $SD = 1.37$), with 67% selecting "Somewhat agree" or "Strongly agree." Likewise, 52% agreed that relying on AI made them less likely to seek feedback from instructors or peers (Q32, $M = 3.11$, $SD = 1.37$). Responses to "I feel less confident discussing technical ideas with others without AI assistance" (Q30) were more evenly spread ($M = 2.22$, $SD = 1.28$), though 23% of respondents still agreed with this statement.

Table 3: Descriptive Statistics for Perceived AI Impact on Skills Items

Item	N	Mean	SD	Min	Max
Q28: AI improved independent debugging	27	2.22	1.19	1.00	4.00
Q29: AI reduced collaborative problem-solving	27	3.56	1.37	1.00	5.00
Q30: Less confident without AI assistance	27	2.22	1.28	1.00	5.00
Q31: AI improved code readability	27	2.48	1.48	1.00	5.00
Q32: AI reduces feedback-seeking	27	3.11	1.37	1.00	5.00

Finally, students were asked how many years of programming experience they had before starting their current programme, ranging from no prior experience to more than three years. This was checked against the three composite psychological scales, the two AI usage measures, and the five items measuring perceived AI impact on skills, with the full set of correlations presented in Table 4.

Prior experience was not related to perceived competence, impostor-type feelings, academic belonging, or either measure of AI use. Among the five items measuring perceived AI impact on skills, two showed a significant relationship with prior experience: students with more prior programming experience were less likely to agree that AI had helped them write more readable and maintainable code ($r_s = -.42$, $p = .031$), and less likely to agree that they felt less confident discussing technical ideas with others without AI assistance ($r_s = -.48$, $p = .011$). The remaining three items, covering debugging, collaborative problem-solving, and feedback-seeking, showed no significant relationship with prior experience.

Table 4: Spearman Correlations Between Prior Programming Experience and Study Variables

Variable	r_s	p	n
Perceived Competence	.15	.449	28
Impostor-Type Feelings	-.04	.850	27
Academic Belonging	.01	.978	27
Passive AI Use	-.02	.932	30
Active AI Use	-.26	.166	30
Q28: AI improved independent debugging	-.09	.657	27
Q29: AI reduced collaborative problem-solving	.01	.977	27
Q30: Less confident without AI assistance	-.48	**.011**	27
Q31: AI improved code readability	-.42	**.031**	27
Q32: AI reduces feedback-seeking	.16	.413	27

4.1.4 Correlations

The relationships between the composite psychological scores and the AI usage sub-scales are visualised in the Spearman correlation heatmap in Figure 1. Spearman's rank-order correlation (r_s) was used to examine these associations.

The three psychological constructs were strongly intercorrelated. Perceived competence and academic belonging shared a significant positive correlation ($r_s = .67$, $p < .001$), indicating that students who reported higher competence also tended to report a stronger sense of belonging. Conversely, impostor-type feelings were significantly and negatively correlated with both perceived competence ($r_s = -.62$, $p < .001$) and academic belonging ($r_s = -.57$, $p < .001$).

Passive and active AI use were significantly and positively correlated with each other ($r_s = .66$, $p < .001$). However, no statistically significant relationships were observed between either AI usage sub-scale and any of the three psychological constructs. Passive AI use showed weak, non-significant negative associations with perceived competence ($r_s = -.30$, $p = .118$), academic belonging ($r_s = -.22$, $p = .270$), and impostor-type feelings ($r_s = -.11$, $p = .573$). Active AI use showed similarly weak and non-significant associations with perceived competence ($r_s = -.20$, $p = .298$), academic belonging ($r_s = -.13$, $p = .520$), and impostor-type feelings ($r_s = -.11$, $p = .580$).

4.1.5 Group Comparisons

Gender Mann-Whitney U tests were conducted to examine whether psychological scores and AI usage habits differed between male and female respondents. Of the valid sample, 21 participants identified as male and 8 identified as female; participants who identified as non-binary ($N = 2$) were omitted from this specific analysis, as the group was too small to support a meaningful statistical comparison. The remaining comparative analysis was therefore restricted to male and

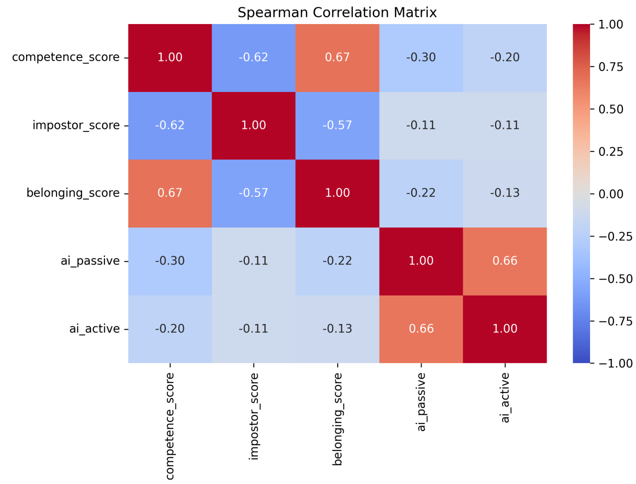

Figure 1: Spearman Correlation Heatmap of Psychological and AI Usage Scores

female respondents. Cross-gender score distributions across the three psychological dimensions are illustrated in Figure 2.

Statistically significant differences were observed across all three baseline psychological constructs. Female students reported higher levels of impostor-type feelings ($M = 3.61$) than male students ($M = 2.10$), $U = 15.5$, $p = .003$. Female students also showed lower academic belonging ($M = 2.84$) compared to male students ($M = 3.95$), $U = 115.0$, $p = .005$, and lower perceived competence ($M = 3.23$) compared to male students ($M = 4.38$), $U = 117.5$, $p = .009$.

In contrast, no statistically significant gender differences were observed for generative AI engagement. Descriptively, female students recorded slightly higher mean scores than male students for both passive AI use ($M_{\text{female}} = 3.12$, $M_{\text{male}} = 2.88$) and active AI use ($M_{\text{female}} = 2.33$, $M_{\text{male}} = 1.92$). However, these differences did not reach statistical significance for either passive use ($U = 73.5$, $p = .618$) or active use ($U = 57.5$, $p = .200$).

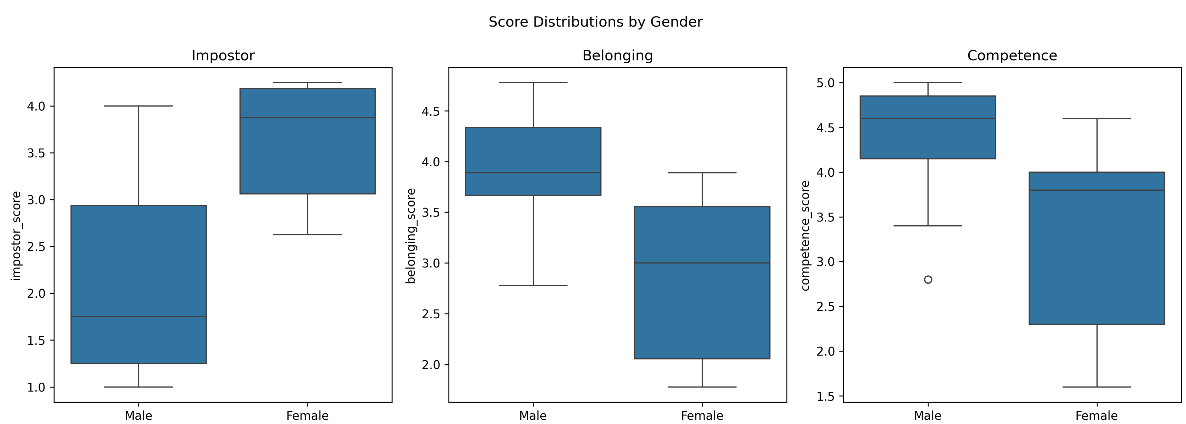

Figure 2: Score Distributions for Impostor Feelings, Academic Belonging, and Perceived Competence by Gender Identity

Academic Year Of the valid sample, 5 participants were in BSc Year 2, 15 in BSc Year 3+, 7 in MSc Year 1, and 4 in MSc Year 2+. A Kruskal-Wallis test was conducted to evaluate score distributions across these academic cohorts. The test revealed no statistically significant differences across academic years for any of the five main variables: impostor-type feelings ($p = .611$), academic belonging ($p = .350$), perceived competence ($p = .710$), passive AI use ($p = .231$), or active AI use ($p = .160$). The complete descriptive mean scores broken down by academic cohort are presented in Table 5.

Descriptively, however, a directional trend was visible in the dataset regarding the progression of generative AI engagement. Within both the Bachelor's and Master's tracks, average scores for both passive and active AI use increased as students advanced through their respective programmes. Specifically, passive use shifted from 2.20 to 3.30 between BSc Year 2 and Year 3+, and from 2.36 to 3.17 between MSc Year 1 and Year 2+. Active AI use followed a similar upward trajectory across year groups within both degree levels, although these descriptive variations did not reach statistical significance.

Table 5: Mean Psychological and AI Usage Scores Across Academic Years

Academic Year	Competence Score	Impostor Score	Belonging Score	Passive AI	Active AI
BSc Year 2	3.40	3.03	3.11	2.20	1.67
BSc Year 3+	4.20	2.46	3.56	3.30	2.04
MSc Year 1	4.47	2.67	4.06	2.36	1.95
MSc Year 2+	3.73	1.92	4.04	3.17	2.78

4.1.6 Qualitative Open-Ended Elaborations

Of the 31 valid survey participants, 11 individual respondents chose to use the optional, open-ended text fields at the end of specific question blocks, resulting in a total of 16 relevant comments. Because these optional text entries were provided by a subset of the sample, they are treated as exploratory illustrations to accompany the quantitative findings rather than stand-alone indicators. These 16 entries were categorised into five descriptive topics.

Theme 1: Generative AI as a Scaffolding and Debugging Partner These comments connect directly to the low active-use scores reported in Section 4.1.3, where no student scored highly on behaviours such as requesting complete solutions or discussing AI-generated code with peers. A group of four respondents provided comments outlining the operational boundaries they apply when using generative AI. Rather than using these tools to complete assignments entirely, these participants described using the software as a concept-explanation or debugging aid to overcome isolated technical barriers:

> "I use generative AI mainly to explain concepts to me to better grasp how to approach the assignment."

> "I tend to resort to genAI when I have run out of ideas on what else I could try, this often occurs when using obscure libraries."

Two respondents explicitly emphasised that they retain complete verification over any automatically generated output:

> "I consider myself to be a responsible user of generative AI... I never let AI generate code without me checking it and at the very least understand it fully."

> "I don't always discuss the outcome with peers, but I always check it myself and never hand it in as is."

Theme 2: Factors Influencing Academic Belonging While the quantitative analysis showed that female respondents reported lower average academic belonging than male respondents, the open-ended comments left by three individual participants illustrate that belonging is an individual experience that can be linked to sub-fields, social circles, or personal traits:

> "I don't really feel like I belong in the coding part but I do feel like I belong to the more human part of AI (alignment, cognitive science and human-AI interaction)."

The remaining two comments within this category linked lower personal belonging scores to introversion or a general disconnection from central student social pipelines:

> "I don't feel much of a communal feeling with my fellow students and other Computer Science people."

> "I don't exactly feel part of a community, but it's also because I've never really been part of the people who actively go to like De Leidsche Flesch or anything, I'm quite introverted."

Theme 3: The Normalisation and Triggers of Impostor Feelings Illustrating the moderate cohort average for impostor-type feelings alongside high individual scores, two separate comments noted that self-doubt is frequently perceived as a common aspect of the Computer Science discipline:

> "I think imposter syndrome is natural. After my 4 years of formal Computer Science study, this is still a thing... completing projects and most importantly being able to learn from seniors will help with feeling like you actually know something."

Furthermore, one respondent pointed to a specific collaborative context where these feelings of academic inadequacy are heightened, highlighting asymmetric group work dynamics:

> "In group projects, I often feel like I am carried through it rather than contributing equally."

Theme 4: Explanations of Self-Worth and Survey Answers Two respondents used the open-ended fields to add a further reflection on the topic of self-doubt, impostor-type feelings and achievement, beyond what the closed survey items could capture. The first student located the source of their self-doubt outside their university work entirely, attributing it instead to a more general sense of self-worth:

> "I feel this has more to do with my self worth more then anything else."

The second student did not think the ideas of earning or deserving success made sense in a university context. They used this view to explain why they chose neutral answers on the survey:

> "I don't think there's such a thing as earning or deserving things in this context, so I filled in 'Neither agree nor disagree' for all questions."

Theme 5: Curriculum Views and Paths to Adoption The comments in this category connect to the descriptive trend observed in Section 4.1.3, where AI use appeared to increase among students further along in their programme. The final three comments focused on how generative AI interacts with the curriculum. One respondent suggested that higher education institutions should adapt evaluation structures to account for the presence of these tools:

> "Uni has to embrace AI and try to change the assignments to facilitate this change."

In contrast, another participant focused on the personal sequence of learning, arguing that baseline programming foundations must be established manually before automated assistance is introduced:

> "I think you need to learn the rules (of programming) before you can break them, and using AI is breaking the rules."

Finally, one student noted that their adoption of generative AI was a recent development, initiated after encountering persistent technical difficulties and receiving an explicit recommendation from others:

> "I've actually never used it in my bachelor, only having started using it very recently due to getting stuck on some things and being recommended to do so."

4.2 Interviews

4.2.1 Participant Profiles

To gain a qualitative understanding of the survey trends, semi-structured interviews were conducted with four students ($N = 4$). Participants P1 and P2 were enrolled in the Computer Science Bachelor's programme, while P3 and P4 were enrolled in the Master's programme. A summary of their academic track levels and their primary AI usage styles is presented in Table 6. To protect participant anonymity within the programme, gender-specific pronouns and specific demographic details have been omitted, and all participants are referred to using gender-neutral terms.

Table 6: Overview of Interview Participant Profiles

ID	Programme Level	AI Usage Style
P1	Bachelor's degree	Conceptual Translation
P2	Bachelor's degree	Targeted Troubleshooting
P3	Master's degree	Early-Stage Scaffolding
P4	Master's degree	Concept Validation

P1 — Conceptual Translation Style P1 used generative AI primarily as an explanatory tool for theoretical concepts rather than for direct code generation. They reported a clear sense of conflict regarding their reliance on the tool, experiencing feelings of academic guilt and a perception that their independent problem-solving skills had decreased. Socially, P1 reported low integration into the university community due to time constraints and personal preferences.

P2 — Targeted Troubleshooting Style P2 used generative AI strictly as a secondary troubleshooting resource when dealing with poorly documented technical frameworks. Their tool usage was self-regulated and deliberate. P2 maintained a high level of confidence in their core programming capabilities and reported that supplementary AI use did not undermine their sense of academic competence. Socially, P2 maintained a small circle of peers and spent limited time on campus.

P3 — Early-Stage Scaffolding Style P3 adopted generative AI recently, driven by the increased workload and perceived difficulty of their current curriculum. They approached the tool with caution, reporting persistent feelings of academic self-doubt and difficulty internalising their academic achievements. P3 valued peer collaboration over automated support.

P4 — Concept Validation Style P4 used generative AI moderately and strictly for high-level brainstorming and basic debugging. They maintained a rigid personal emphasis on institutional rule-following and expressed strong criticism toward peers who rely heavily on automated systems to complete assignments. Socially, P4 maintained a strict separation between their academic and personal life, drawing their primary social connections from outside the university environment.

4.2.2 Thematic Findings

The qualitative data from the semi-structured interviews were analysed using inductive thematic analysis. The findings are structured into major themes that capture broad patterns across the sample, with individual participant experiences used within each theme to illustrate how these concepts manifest in practice.

Theme 1: AI Usage as a Response to Time and Institutional Pressures

The interview data showed that, in their own accounts, students primarily used generative AI to manage external pressures such as time constraints, fast-paced curricula, and immediate technical difficulties. As they described it, participants turned to these tools as a practical resource when standard university support structures were unavailable, rather than as a way of avoiding critical thinking.

Participants reported that academic deadlines influenced how they used generative tools. P1 noted that they used generative AI when facing short submission windows. Specifically, when real-time teaching assistant (TA) or professor support was unavailable outside of university hours, P1 used the software to resolve complex coding errors. This pragmatic framing is captured clearly in P1's own words: *"It's right before the deadline so it's too late to be asking a question. Stuff like that gets in the way. And at that point, if you can't get it, then you're just not passing the assignment."*

In contrast, P2 described using a highly restricted approach, using generative AI only as a last resort. As they explained it, P2 limited their tool usage to troubleshooting specific, niche programming libraries when official technical documentation failed to provide clear answers. As P2 described it: *"Once I've run out of easily accessible options, I turn to that to see if that can give me anything."* For both Bachelor's degree participants, the AI tool deployment was framed as a direct reaction to limited time and available documentation.

For Master's degree participants, the transition into the Master's track introduced structural difficulties that, as they described it, altered their learning pace. P3 identified increased time pressure as the main driver for adopting generative AI. Facing what they experienced as a steep learning curve in their specific track, P3 used the tool to understand unfamiliar programming domains, using the software's explanations to establish an initial understanding of the code. Due to tight submission schedules, P3 said they used the tool to resolve complex debugging errors quickly, noting that frequent deadlines restricted the time available for independent troubleshooting in their experience. P3 described independent debugging as something they genuinely enjoy, saying *"I find that really interesting to do,"* but explained that time pressure made it impractical to rely on this approach as often as they would have liked, pushing them toward AI assistance instead.

Similarly, P4 described using the tool to manage time pressure and mental fatigue. P4 limited their generative AI use to debugging and high-level brainstorming, by their own account. They said they rarely used automated code generation; when they did, they described treating the output as a temporary reference to verify if a specific logic path was viable before writing their own code independently.

Theme 2: Code Authorship, Ownership, and Personal Competence The integration of generative AI into programming tasks created practical questions regarding code authorship and intellectual ownership, at least as participants experienced it. Even when using the tools for efficiency, participants reported a decreased sense of personal pride in work completed with AI assistance. To maintain confidence in their programming skills, students set their own personal rules to keep control over their final submissions.

The boundary between automated assistance and independent work was, in their own accounts, clearly defined by the participants. P1 compared programming with AI to solving a puzzle, noting that receiving a complete, ready-made solution reduced their personal satisfaction in completing an assignment: *"It kind of feels the same way as solving a Sudoku by looking up the answers."* Because P1 associated independent problem-solving with personal pride, they said they actively avoided raw code generation to protect what they saw as their identity as an independent programmer.

For P2, needing to use generative AI initially caused, by their own account, a reduction in personal comfort. However, P2 described managing feelings of diminished pride by treating the tool strictly as an informational reference source. As they described it, they maintained code ownership through an iterative process of review and modification: by reading through the generated code, editing it, and restructuring it manually, P2 said they processed the underlying material until the final implementation felt like their own independent work. P2 summarised this approach clearly: *"Ideally, once you've used it for one problem, you have more knowledge to work from on your own, so you have to use it less."*

P3 described maintaining a clear personal boundary regarding intellectual ownership. Rather than allowing generative models to dictate the structural design of their projects, P3 said they restricted their AI usage to ensure that their core conceptual contributions remained entirely their own. In their view, this approach allowed them to protect their role as the primary author of their assignments, though this topic was less central during P3's interview than for the other participants.

P4 described maintaining a strict separation between automated outputs and their final submissions by keeping the tool completely decoupled from their working files. P4 said they limited their interaction with generative models to checking proof-of-concept code. Once the model demonstrated, in their view, that a specific architectural design or logic path was functional, P4 said they deleted the software's output entirely. By starting with a blank file and using manual rewriting to complete the actual implementation, P4 described ensuring that the final problem-solving breakthrough remained theirs, which they said preserved their pride in the finished product.

Theme 3: Perceptions of Competence, Self-Doubt, and Impostor Feelings The interview data revealed a distinct divide in how students perceive their own academic capabilities and position within their cohort when using generative AI. For two participants, relying on algorithmic assistance increased personal insecurity and self-doubt, in their own accounts, while for the other two, a stable baseline of confidence in their technical skills appeared to act as a buffer against impostor feelings.

P1 reported that regular use of generative tools negatively affected their confidence. Rather than viewing the tool as an efficiency booster, P1 said they interpreted their reliance on it as a source of academic inadequacy. They expressed a persistent concern that outsourcing complex logic problems to a large language model might weaken their independent problem-solving skills and critical thinking over time: *"I do think for a problem solved with code, I feel like I've gotten worse at that because I have been using AI."* This reliance, in their view, compounded pre-existing insecurities, making them feel academically less capable than their peers despite their actual performance. As P1 put it: *"the problem-solving part of being a computer science student is kind of not being done by me, which does kind of make me feel a bit like an imposter."*

In contrast, P3's academic self-doubt was, by their own account, closely tied to social and demographic comparisons within the cohort. When entering the Master's programme, P3 said they frequently benchmarked their progress against high-achieving peers, which led them to downplay their own academic milestones and attribute their progression to luck rather than skill: *"It really feels like I just got here by luck. I went through my Bachelor's just somehow."* However, P3 described using generative AI as having eased this feeling: by noticing that many of their classmates, including ones they saw as high-achieving, also relied on AI tools to keep pace with lectures, P3 came to see their own AI use and struggle to keep up as less of a sign of personal inadequacy. This observation, in their experience, made the pace of the cohort feel more attainable, and P3 subsequently used the technology as a practical way to manage the heavy workload and reduce the gap they felt between themselves and their peers.

Participants P2 and P4 stood in contrast to this psychological strain, describing a higher resilience to self-doubt related to AI use. P2 said they experienced only minor, temporary doubts related to their thesis work, which they described quickly resolving by relying on a stable internal sense of competence. They evaluated their coding skills against the broader student body by reasoning, in their own words, that their abilities were comfortably on par with or above the average student, which they said validated their sense of academic belonging.

P4 described a similarly resilient profile, reporting no notable impostor feelings. Having come from a demanding educational background, P4 said they judged academic success mainly by results, such as grades and exam performance, rather than by how a task felt to complete. While they occasionally experienced minor frustration when an AI tool resolved a bug they could not fix immediately, their confidence in their place within the programme remained stable, in their account. Their sense of belonging was supported, by their own description, by consistent academic results and exam readiness, and they did not report the kind of self-doubt described by the other participants. This focus on results over feeling is reflected in how P4 framed their own competence: *"Emotionally it feels like it does not affect me, but rationally I know it probably does because it does for everyone."*

Theme 4: Cohort Fragmentation and Physical Presence on Campus Three of the four participants described reducing how much time they spent physically on campus, instead relying more on independent study at home.

P1 was an example of a student spending less time on campus. They frequently chose to study at home rather than entering the Computer Science building, which contributed to a decrease in peer collaboration and a reported lack of community connection. However, P1 clarified that this was a personal habit that existed prior to and independently of their generative AI use. Consequently, while P1 relied on successful grades to prove they belonged academically, they described a very low sense of social belonging within the student community.

P2's reduced time on campus was driven primarily by long commuting times. Separately, P2 described being a generally shy person who preferred working within a small, trusted group of friends, a preference they said existed independently of the commute. They relied on their own study milestones and private routines to track their progress and confidence.

P3 also described spending less time on campus, though their account of belonging combined this with active efforts to support community-building among new Master's students. They also described feeling somewhat out of place as a computer science student, seeing themselves as more of a humanities-minded person, which was part of why they spent less time on campus.

P4 did not describe any change in how they engaged with campus life, even while recognising a general decline in cohort cohesion and student attendance around them. P4 kept their academic work separate from their personal life, drawing their main social fulfilment from an external sports association. They described believing that strong academic results and technical skill are the main things a student needs to belong, showing little interest in a shared communal academic identity.

For the female-identifying participant, physical presence on campus involved a careful balance of personal comfort and identity within the university environment. As a minority student in a historically homogeneous field, this participant described feeling highly visible when navigating the physical faculty building, including feeling that standing out by dressing in a particularly feminine way drew attention. To manage this, they reduced their time on campus. However, this did not mean complete isolation; this participant described encountering female role models within their studies as having made them feel significantly more comfortable.

Theme 5: Moral Perspectives and Peer Dynamics Regarding AI Use A clear difference between participants was visible in the informal rules, moral views, and peer judgements they described around generative AI use. P1 described experiencing internal conflict and shame around their own use, while also judging peers whose use seemed excessive. P2 described feeling no such conflict at all. P3 and P4 both described judging peers who relied heavily on AI, seeing their own use, by contrast, as limited and carefully bounded.

P1 described a clear sense of moral and emotional conflict around their generative AI use. Facing strict institutional discouragement, P1 said they felt academic guilt, which led them to hide their AI use from others: *"It kind of feels like a dirty secret I should not talk about."* However, P1 also judged their peers by a similar standard. They said they saw classmates as less authentic computer science students if their reliance on AI seemed too visible or excessive, and admitted they would judge a peer's code more critically in a group project specifically to check whether AI use was too obvious. This created what looked like a cycle: P1 hid their own habits to avoid being judged the same way, while applying that same judgement to others.

In contrast, P2 described no ethical or emotional conflict at all when using generative tools. P2 said they viewed large language models as a standard engineering tool rather than a moral issue. They described keeping their own approach separate from their peers' opinions, feeling no academic shame, and judging the tool purely by how useful it was in practice.

P3 approached the moral side of generative AI differently, placing more weight on peer connection and fairness. They described staying cautious about shortcuts, worried this might weaken their skills over the long run, and said they preferred learning with peers over relying on software. In their view, getting help from another person felt more meaningful than getting help from AI, since it also eased the isolation some students experience. P3 also said that finishing a degree by relying almost entirely on AI gives an unfair advantage, since it devalues the effort of students who do the work themselves: *"Imagine you're writing this nice essay and someone else just auto-generates it. It feels like your effort was tainted because of that."*

Finally, P4 held a strict, merit-based view, believing that academic credentials should be earned through one's own effort. In group projects, they set clear boundaries around how AI could be used. When teammates submitted work that relied obviously on generative AI, P4 said they intervened directly: *"This is basically all AI. Please write it without it."* This, in their account, let the group avoid drawing formal institutional attention. If a group member kept using AI in a way that crossed this line, P4 said they distanced themselves socially from that person. They described this not as a personal conflict, but as a principled response to what they saw as a clear failure of academic integrity: *"I do not respect them if they use a lot of AI for study programmes because I feel like that just means that they can't do it themselves. In my opinion, they don't belong here if they only use that for all their work."*

5 Discussion

This study set out to examine how generative AI use relates to Computer Science students' sense of academic belonging and perceived legitimacy, using a survey to identify broad patterns and interviews to help explain them. This chapter discusses the findings in that order. Section 5.1 addresses SQ1, looking at which tools students use and how. Section 5.2 addresses SQ2, looking at how AI use relates to impostor-type feelings and perceived competence. Section 5.3 addresses SQ3, looking at how students perceive AI's impact on specific skills. Section 5.4 then returns to the main research question, bringing these three parts together. Throughout, the survey results are treated as the primary evidence, with the interviews used to illustrate and help explain those results rather than as an equally weighted source of their own.

5.1 AI Use Patterns

Within this sample, AI use was widespread but uneven. Most students reported using AI for coding assignments at least sometimes, while a smaller group reported never using it. Even within a single, fairly homogeneous student population, adoption of these tools is far from universal, and a meaningful minority of students appear to be getting through their Computer Science education without leaning on generative AI at all.

Among students who do use AI, the survey distinguished between two measures: a passive measure, capturing general frequency of use and reliance on AI when stuck, and a more active measure, capturing whether students ask AI to generate full solutions, use it to debug, or discuss its output with peers. Scores on the passive measure were consistently higher than scores on the active measure, and no student in the sample scored highly to begin with on the active measure. Students in this sample, in other words, turn to AI often and lean on it when stuck, but rarely take the further steps of asking it for a complete solution, using it specifically to debug, or discussing what it produces with peers.

The interviews illustrate what this gap between the two measures can look like for an individual student, without establishing that this is the dominant pattern across the sample. P1 described using AI frequently when stuck or wanting a concept explained, consistent with a high passive score, while explicitly avoiding requests for full solutions. P3 described a similar frequency of use when struggling with unfamiliar material in their Master's coursework, also without requesting complete solutions. Both accounts show one way these two scores can move independently of each other: a student can rely on AI often when stuck, without that reliance taking the specific form the active measure captures.

This gap should not automatically be read as reassuring. Relying on AI when stuck can still amount to AI doing a substantial part of the problem-solving, even where that reliance never takes the form of a literal request for a complete solution. A low score on the active measure shows only that a student does not often ask AI for a full solution, does not often use it specifically to debug, and does not often discuss its output with peers; it says nothing about how much the more frequent, passive use actually shaped the final work. Several open-ended survey responses suggest that at least some students are conscious of this distinction and try to manage it deliberately, with one student stating they never let AI generate code without checking and fully understanding it themselves, and another describing programming fundamentals as something that needs to be learned before AI is introduced. These comments suggest the gap between the two measures is, for some students, a deliberate boundary. They do not establish that this is true of the sample as a whole, since they describe how a handful of students chose to characterise their own use rather than confirming what happened in practice.

A related pattern in the survey was that most students reported never discussing AI-generated code with their peers, one of the three behaviours making up the active measure, pointing to AI use being a largely solitary practice within this sample. This is returned to in Section 5.3, where AI's perceived effect on collaboration is discussed in more detail. There was also a visible trend toward higher scores on both measures among students further along in their programme, both at Bachelor's and Master's level, though this trend was not strong enough to be confirmed statistically. The most likely explanation is developmental: AI use increases as coursework becomes harder and time becomes scarcer. The interviews support this directly. P3 described adopting AI only recently, in response to the heavier workload of starting the Master's programme, while P2 described using AI less over time as their own underlying skills developed. These accounts pull in different directions, one toward more reliance over time and one toward less, which fits a trend that was visible but not strong enough in the descriptive data to draw a single firm conclusion from.

The pattern observed here, frequent reliance on AI when stuck alongside comparatively rare engagement in the more specific behaviours captured by the active measure, is difficult to compare directly to earlier findings in the literature, since the samples differ considerably in experience level. Amoozadeh et al. [2] found that a substantial share of introductory CS1 students submitted work generated directly by AI with little independent effort, while Prather et al. [20] found a similar pattern among novice programmers more broadly, who were prone to finishing tasks with a false sense of having understood the material. Both studies focused specifically on students at the very beginning of their Computer Science education, whereas the present sample consisted entirely of second-year Bachelor's students and above. It is possible that the more cautious pattern observed here reflects this difference in experience level: students further along in a Computer Science programme may have already developed habits or judgement that introductory students have not yet had the chance to form. It is equally possible that the riskier patterns described by Amoozadeh et al. and Prather et al. [2, 20] are also present among more experienced students in this sample, but were simply not visible in this particular dataset, whether because such students were less likely to take part in a voluntary survey or less likely to describe their use candidly. The present data cannot distinguish between these possibilities, and the absence of a clearly risky pattern here should not be read as evidence that it does not exist in this population, particularly given that the comparison group in the existing literature was, in each case, considerably less experienced.

The more cautious pattern observed here does, however, align with findings from recent studies conducted within the same LIACS community. Gorter [14] found that students at Leiden University described using AI primarily for efficiency and to resolve specific technical obstacles, particularly when other support was unavailable. Visser [29] similarly found that LIACS students used AI mainly to support rather than replace their work, with productivity and accessibility as the dominant motivations. That broadly similar patterns appear across multiple studies conducted within the same institution suggests they may reflect something specific to this environment, rather than being incidental features of any one sample.

These usage patterns show that students in this sample turn to AI often, but rarely engage in the more specific behaviours of requesting full solutions, debugging with it, or discussing its output with peers. What this gap means for students' underlying independence cannot be settled by how often AI is used. It may reflect a genuinely cautious pattern of use, a less cautious one that simply does not surface in measures of frequency, or something that differs from one student to the next; the present data does not favour one of these over the others. What can be said with more confidence is that frequency alone, the variable this section has focused on, is not a strong enough basis on which to judge how independently students are actually working. The next section turns to dependence more directly, asking how that question plays out for students' sense of their own competence.

5.2 Frequency, Dependence, and Psychological Wellbeing

On average, students in this sample reported high competence and only moderate impostor-type feelings. These averages sit alongside considerable individual variation, and the interview profiles illustrate what that variation can look like in practice. P1 described a persistent sense of having gotten worse at problem-solving and feeling like an impostor as a direct result, while P2 and P4 described a stable sense of competence that did not appear to be shaken by their AI use at all. The psychological experience of being a Computer Science student in this context clearly varies between individuals, and that variation was visible before AI use is considered at all.

This variation matters for how the survey's central finding on AI use should be read. Neither measure of AI use, the passive measure capturing frequency and reliance when stuck, nor the active measure capturing solution requests, debugging, and peer discussion, was related to students' perceived competence or impostor-type feelings, though the direction of the relationship was consistently negative across every comparison. The two psychological constructs themselves were strongly related to one another: students reporting higher competence also reported markedly fewer impostor-type feelings. AI use, in other words, failed to predict either of two constructs that are otherwise closely tied to each other in this sample, which makes the absence of a relationship more notable than it might be if competence and impostor-type feelings were only loosely connected to begin with.

As discussed in Section 5.1, this reliance may extend further into the actual problem-solving than the frequency data alone can show, particularly since students who lean on AI most when stuck also tend to be the ones engaging most with what it produces, rather than these being two separate groups. Neither measure was designed to capture this directly.

The interviews illustrate what this can look like for individual students. P2 described working through AI output line by line until the underlying logic felt like their own, a process they described as one that, ideally, leaves a student needing the tool less over time rather than more. P4 described a stricter routine, checking AI output against a specific problem before discarding it and rewriting the final implementation independently. P1 described no equivalent routine, and instead described the problem-solving side of their coursework as something that was no longer really being done by them. P3 described a different relationship between AI use and impostor-type feelings altogether: consistent with the persistent self-doubt and difficulty internalising achievements described in their profile, rather than affecting their sense of doing the work themselves, AI use made them realise that many of their classmates also relied on AI to keep pace, which helped ease a tendency to attribute their own progress to luck rather than ability.

This explanation is one possibility, not a conclusion the data can establish, and it is equally possible that no meaningful relationship between AI use and these two constructs exists in this sample at all, with the consistent negative direction of the correlations simply reflecting noise in a small dataset. The direction of any relationship that does exist is also difficult to establish from this data. One open-ended survey response is a reminder of how much can sit outside this relationship altogether: one respondent attributed their self-doubt to a general sense of self-worth rather than anything specific to their studies, suggesting that AI use and negative feelings about one's abilities may, for some students, reinforce each other without either clearly causing the other. If dependence does play a role, however, Self-Determination Theory offers one account of why it might matter: a sense of competence depends on genuinely experiencing mastery over a task, not merely on completing it [23]. Read this way, a student can finish an assignment successfully while still feeling that the mastery underlying that success was not their own, because the task was completed with the tool rather than through their own reasoning, which fits P1's account closely.

The survey also showed a clear gender difference on both constructs discussed in this section: female students reported markedly lower perceived competence and higher impostor-type feelings than male students, in line with the broader pattern of gender differences in impostor-type feelings already discussed in Section 2.2 [21, 7]. This difference existed independently of AI use, since no comparable gender difference was found in either measure of AI use. Whatever is driving the lower competence and higher impostor-type feelings reported by female students in this sample, it does not appear to be explained by how often or how actively they used generative AI. The female-identifying participant's account offers a brief illustration of how competence and AI use can still intersect for a student navigating a stronger sense of under-representation: this participant described adopting AI specifically after starting to feel behind their peers, framing their use less as a convenience and more as a way of closing a gap they already felt existed. This is a single account and cannot be generalised to the broader gender difference found in the survey, but it suggests one way that comparable AI use might carry a different meaning for competence depending on the security of a student's existing position in the field. The relationship between gender, AI use, and belonging more broadly is taken up further in Section 5.4.

AI use in this sample does not appear to be a major factor behind either the general level of competence and impostor-type feelings reported, or the clear gender difference observed in both. Whether dependence, as distinct from frequency, plays the role suggested by some of the interview accounts, or whether competence and impostor-type feelings in this sample are simply unrelated to AI use, is a question the present data can raise but not answer. The next section turns from these two constructs to how students perceive AI's effect on specific competencies.

5.3 Perceived Impact on Specific Competencies

The five survey items measuring perceived AI impact on skills did not form a single coherent construct, which is itself informative for this question. Students do not appear to experience AI's effect on their abilities as one undifferentiated thing; instead, the pattern of responses splits along a fairly clear line between items concerning individual technical skill and items concerning interaction with other people.

Of the two items concerning individual technical skill, improved debugging and improved code readability, neither received a clear majority response in the survey. Debugging is a particularly interesting case among the two, since the interviews offer a detailed picture of how students approached it individually. P1 noted that their debugging approach had not changed with AI adoption, still relying on print statements to trace errors, whilst simultaneously feeling that their higher-level problem-solving had deteriorated. P3, by contrast, described using AI specifically to offload complex debugging tasks under time pressure, particularly for difficult error types such as memory errors in CUDA, whilst retaining independent control over simpler debugging processes. P2 described a comparable kind of boundary, turning to AI only as a last resort for poorly documented libraries and otherwise treating their debugging process as untouched by AI at all. What connects these three otherwise quite different accounts is that each participant drew a clear line between the areas where AI assistance felt acceptable and those where it did not. This pattern is not obviously undermined by prior experience: how much programming experience a student had before starting their programme showed no relationship with whether they felt AI had improved their debugging, suggesting the split on this item is not simply a matter of more experienced students having less room to improve.

The picture looks different for perceived improvements in code readability, where students with more prior programming experience were less likely to say AI had helped. Here, at least part of the split may genuinely reflect where a student started rather than a deliberate choice about AI use, since a student who already writes readable code has less for AI to improve in the first place. The same kind of deliberate boundary-drawing visible in the interviews for debugging does not appear to extend equally to every technical item the survey asked about.

The three items concerning collaboration and feedback-seeking, covering reduced collaborative problem-solving, reduced confidence discussing technical ideas without AI, and reduced inclination to seek feedback from others, showed a clearer pattern, with a majority of students agreeing that AI use had reduced these behaviours. Each of these three items concerns a student's interaction with other people, in contrast to the two items discussed above, which concern a student's own technical output. This pattern connects directly to the finding in Section 5.1 that most students reported never discussing AI-generated code with peers, suggesting AI use displaces peer interaction specifically, more consistently than it displaces or improves any particular technical skill. P1's account illustrates this directly, describing a noticeable decline in the kind of collaborative troubleshooting they used to do with classmates before adopting AI. P3 and P4, by contrast, each described an explicit preference for human support and peer consultation over AI, treating peer interaction as the more valuable resource even where AI was readily available. The direction of this relationship is not obvious, however. It is possible that AI use causes a reduction in collaboration, as P1's account suggests, with a tool gradually substituting for conversations that used to happen with peers. It is equally possible that the relationship runs the other way, with students who are already less inclined to seek out peers or ask for feedback turning to AI precisely because it offers a private alternative to a kind of interaction they were avoiding regardless. P3 and P4's comparative comfort with peer interaction, paired with relatively measured AI use in both cases, is consistent with either direction, and the survey, which only measures AI use and the reduction in collaboration at the same point in time, cannot establish which came first.

It is possible that AI genuinely affects collaboration more consistently than it affects technical skill, because asking a peer and asking an AI tool serve a similar function and are more easily substituted for one another than a skill like debugging can be replaced outright. It is equally possible that this apparent split simply reflects which five items happened to be asked, and that a differently worded set of technical items would have produced a similarly clear pattern. The present data cannot distinguish between an effect that is genuinely concentrated in collaboration and an artefact of item selection.

These findings suggest that AI's perceived impact on competence is not a single dimension running from helpful to harmful, but something that depends on the specific skill or behaviour in question. Prior programming experience offers a partial, rather than complete, account of this variation: it appears to matter for how much room students feel AI has to improve their code and how confident they feel without it in conversation, but not for debugging, collaboration, or feedback-seeking directly. What it cannot do is settle whether the remaining split between technical and social competencies reflects something real about how AI affects these two kinds of skill differently, or simply which five items this particular survey happened to ask.

5.4 Generative AI Use and Academic Belonging

Having considered AI use patterns, their relationship to competence and impostor-type feelings, and their relationship to specific competencies in turn, this section returns to the main research question: how does generative AI use shape Computer Science students' academic sense of belonging and perceived legitimacy within their field. Three mechanisms emerge from the findings discussed so far, concerning the displacement of peer interaction, the role of autonomy and ownership in AI-assisted work, and the uneven distribution of belonging along gender and identity lines.

The first mechanism concerns peer interaction. Most students in this sample reported never discussing AI-generated code with peers, and a majority agreed that AI use had reduced their collaborative problem-solving with others, findings discussed in detail in Sections 5.1 and 5.3.

This matters directly for belonging, since Perlmutter et al. [19] identify safety, the ability to ask questions and make mistakes without fear of judgement, and access, the practical and social conditions, including networks of peers, that enable meaningful participation in the CS community, as components of CS belonging specifically.

Both are built through exactly the kind of peer interaction that appears reduced here. Whichever direction the relationship runs (Section 5.3), the practical effect on belonging may be similar: less of the collaborative, judgement-free interaction through which safety and membership are built, a pattern P1's account of declining collaboration illustrates even where, as they themselves noted, it sits alongside a withdrawal from campus life that predated their AI use. Safety can also be undermined even where peer interaction does take place: one open-ended survey response described feeling, in group projects, that they were carried through the work rather than contributing equally, suggesting that the quality of collaboration matters as much as its frequency.

The interviews point to a further, related dynamic that the survey did not measure at all, though it appeared in only two of the four accounts and took different forms in each. P1 described hiding their own AI use from peers out of a sense of guilt, whilst simultaneously judging classmates whose reliance on AI seemed too visible. P4 took a more direct approach, confronting groupmates over AI-generated contributions and socially distancing from those who continued to rely on it. Despite this difference in expression, both suggest that AI use can become a criterion by which students judge each other's legitimacy as computer scientists, which would erode the same safety that reduced collaboration already threatens. Given that this rests on two accounts within an interview sample of four, it is best read as a possibility this study surfaces rather than a pattern it establishes, and no equivalent item exists in the survey to test it more broadly.

The second mechanism concerns autonomy. Self-Determination Theory identifies autonomy, alongside competence and relatedness, as one of the three basic psychological needs underlying belonging and motivation [23], yet the findings discussed in Sections 5.1 and 5.3 are really about this need even where they were not framed in these terms. The boundaries students described drawing around their own AI use, P1 avoiding ready-made solutions because it felt like solving a puzzle by looking up the answer, P4 discarding AI output and rewriting code independently, and the open-ended survey comments describing a refusal to submit AI-generated code without fully understanding it first, can be read as attempts to preserve a sense of self-directed work rather than simply as caution about academic integrity. Where this sense of authorship was missing, as in P1's account of feeling that the problem-solving side of their coursework was no longer something they themselves were doing, the cost was not just lower perceived competence but a more direct sense of not being a legitimate computer scientist, the impostor-type feelings discussed in Section 5.2. Read through this lens, the individual, often idiosyncratic boundaries students draw around AI use are not incidental details of how they happen to work, but a visible attempt to protect the autonomy that SDT [23] identifies as central to belonging in the first place.

The third mechanism concerns the uneven distribution of belonging itself. The survey showed a clear gender difference across all three psychological constructs, discussed in Section 5.2, with no corresponding difference in AI use. This means the same pattern of AI use does not sit on equal ground for every student: a student who already feels less secure in their competence and legitimacy, for reasons unrelated to AI, brings that insecurity to their use of these tools regardless of how often or how actively they use them. As introduced in Section 5.2, the female-identifying participant's account extends beyond competence into belonging more broadly: encountering more demographic diversity and female role models in the programme shaped their wider sense of fitting into the discipline, suggesting the same factors that made AI feel like a useful response to insecurity were also tied to belonging itself.

What these patterns suggest, taken together, is that AI use may not straightforwardly undermine belonging, but could instead make it more uneven. Students who already occupy a secure position within the discipline appear, in the accounts gathered here, to be largely insulated from its psychological costs, able to use these tools for efficiency without much at stake. For those who do not, whether because of pre-existing self-doubt, identity-related vulnerability, or a tendency to experience AI as substituting for their own thinking rather than supporting it, the same tools may quietly deepen the precariousness of their position. The mechanisms through which this happens appear to differ across individuals, though three recur across the present data: the displacement of peer interaction through which safety is normally built, the role AI use plays in supporting or undermining a student's sense of autonomy over their own work, and the uneven position from which different students approach these tools in the first place. One underlying interpretation is consistent across them: belonging in Computer Science was already unevenly distributed before generative AI arrived, and the present data suggests that its integration may have done little to change that, and in some cases may even have sharpened it.

5.5 Limitations

Whilst the present study offers a rich, mixed-methods account of how generative AI use relates to Computer Science students' psychological experience and sense of belonging, several limitations should be considered when interpreting the findings.

The most consequential limitation concerns sample size. With 31 valid survey respondents and four interview participants, the study was likely underpowered to detect small to moderate effect sizes in the correlational analysis, and the results reported in this study should be read with this in mind. This is particularly relevant to the gender comparisons reported in Section 4.1.5, where the female and non-binary subgroups were considerably smaller than the male subgroup, and to any analysis broken down by programme, where some programmes were represented by only one or two respondents. The interview sample, whilst sufficient for an exploratory study of this scope, limits the range of perspectives captured, and the interview findings should be understood as illustrative of possible patterns rather than exhaustive accounts of the LIACS student experience. Relatedly, the interview sample consisted entirely of final-year Bachelor's and Master's students, leaving the perspectives of earlier-year students, among whom AI adoption patterns and psychological responses may look quite different, entirely unrepresented in the qualitative data. One mechanism discussed in Section 5.4, concerning informal moral judgements around AI use, rests entirely on the interview accounts and has no equivalent item in the survey; it should be read as a pattern visible within this small sample rather than an established feature of the wider cohort.

The study's reliance on self-reported data introduces a further source of potential bias. P1's description of AI use as a dirty secret they felt uncomfortable disclosing suggests that institutional stigma may lead students to under-report their actual usage, which would in turn attenuate any observed correlations between AI use and the psychological constructs. This concern is discussed in more depth in Section 5.1 and Section 5.2, where the possibility that interview accounts of disciplined or cautious AI use are themselves favourable self-presentations is considered directly.

The quantitative instrument carries a related limitation: the passive versus active measure distinction captures frequency rather than the meaning students assign to their use or the degree of dependence they experience, dimensions that the discussion suggests may be more psychologically consequential than frequency alone. Similarly, the five items measuring perceived AI impact on skills did not form a single coherent construct, and the technical/relational split used to organise the discussion of these items in Section 5.3 reflects the content of the items themselves rather than a statistically confirmed distinction.

Two demographic variables collected in the survey, international student status and functional impairment, could not be meaningfully analysed. Only one respondent identified as an international student, and disclosed rates of functional impairment were too low to support reliable comparison without risking the identifiability of individual respondents; both variables were therefore excluded from the quantitative analysis.

Finally, the cross-sectional design means the findings represent a snapshot at a single point in time, and cannot speak to how AI use and its psychological consequences develop as students progress through their degree. A longitudinal design would be better placed to examine these dynamics over time. The study's focus on the LIACS community at Leiden University was a deliberate choice rather than an incidental constraint, allowing for a contextually grounded account of one specific Computer Science programme. The findings are therefore best understood as insights into this particular community, and their transferability to other institutional or national contexts remains an open question for future research.

6 Conclusions and Further Research

The present study set out to examine how generative AI use shapes Computer Science students' sense of belonging and perceived legitimacy within their field, combining a quantitative survey with in-depth qualitative interviews within the specific context of the LIACS community at Leiden University. A complex and diverse picture has emerged: generative AI use appears neither to straightforwardly undermine nor to straightforwardly support students' psychological experience of the discipline, and its effects seem to depend heavily on context and on the individual student.

Regarding the first sub-question, generative AI use within this cohort appears widespread and primarily driven by time pressure and institutional constraints rather than a desire to avoid independent thinking. Usage also appears to develop as students progress through their programme, suggesting that engagement with these tools is shaped as much by the demands of the curriculum as by individual choice.

Regarding the second sub-question, neither measure of AI use was related to perceived competence or impostor-type feelings. This may reflect a genuine absence of relationship in this sample, or it may reflect that frequency of use does not capture what matters most psychologically: whether students experience their use as substituting for their own thinking or as supporting it. The present data cannot determine which of these is closer to the truth. What can be said is that perceived dependence and cognitive ownership over one's work emerged as potentially more consequential dimensions than frequency alone, and that Self-Determination Theory's view that competence requires genuinely experienced mastery rather than merely completed tasks [23] may help explain why, if a relationship does exist.

Addressing the third sub-question, students' perceived experience of AI's impact on their competencies was not uniform. Individual technical skills, including debugging, code readability, and confidence in technical communication, were experienced in highly individual and context-dependent ways. By contrast, the perceived reduction in collaborative and feedback-seeking behaviours showed a clearer and more consistent pattern across the sample. To the extent that AI use affects competence development in this cohort, its most visible cost appears to be social rather than technical: a gradual displacement of the peer interaction through which both skills and belonging are built.

Returning to the central research question, the study suggests that generative AI use shapes Computer Science students' sense of belonging and perceived legitimacy through three interconnected patterns. AI use appears to erode belonging by displacing the peer interactions through which relatedness is built, though the causal direction of this relationship is ambiguous and may in some cases reflect pre-existing isolation rather than a direct consequence of AI adoption. Informal moral judgements among students about legitimate AI use appear to introduce new criteria for membership, making the social environment feel less safe for some, though this pattern rests on a small number of interview accounts and should be read with appropriate caution. At the same time, belonging remains unevenly distributed along gender and identity lines, and the present findings raise the possibility that identical patterns of AI use may carry different meanings depending on the position a student already occupies within the discipline. Together, these patterns point toward a consistent underlying dynamic: belonging in Computer Science was already unevenly distributed before generative AI arrived, and the present findings suggest that its integration may have done little to change that.

The findings also carry a number of practical implications for the LIACS community. The observation that students use generative AI despite institutional prohibition suggests that blanket policies may be less effective than guidance focused on how students engage with these tools. Since what appears to matter psychologically is not how often AI is used but whether students maintain cognitive ownership over their work, guidance that helps students reflect on their relationship with AI output may be more meaningful than policies centred on frequency or prohibition alone. Additionally, the gender differences observed across all three psychological constructs existed independently of AI use, suggesting that belonging interventions at LIACS cannot address the belonging gap by focusing on AI alone. Support structures that address structural and identity-related factors directly, such as mentorship, visible representation, and spaces where legitimacy is affirmed rather than assumed, may be more effective than interventions focused narrowly on AI use patterns.

Several directions for further research emerge from these findings. Most immediately, a larger and more demographically diverse sample would allow for a more reliable test of the correlational relationships suggested by the present data, and would make it possible to examine whether the relationship between AI use and psychological experience differs meaningfully across gender, academic year, and programme track. A longitudinal design would be particularly valuable given the evidence that AI adoption is a developmental process: the psychological consequences of tool use may shift considerably as students gain experience and progress through their degree, and a cross-sectional design cannot speak to this trajectory. Future quantitative work would also benefit from developing instruments that more directly capture students' subjective experience of dependence, their sense of cognitive ownership over AI-assisted work, and the social contexts in which that use takes place, dimensions that the present study's qualitative data suggests may be more psychologically meaningful than usage patterns alone. The possibility that male and female students turn to these tools for fundamentally different reasons, even when their broader patterns of use and psychological self-reports look similar on the surface, deserves dedicated empirical attention in future work. Finally, the moral hierarchy and peer policing dynamics identified in the qualitative data represent an under-explored dimension of the generative AI literature. Understanding how informal judgments around AI use shape the safety and inclusivity of Computer Science learning environments is a question that future qualitative work, conducted across a wider range of institutional contexts, might productively examine.

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Introduction

. Generative AI Use and Sense of Belonging in CS Education

My name is Alissia Reemeijer and I am a Bachelor's student in Computer Science at Leiden University. This survey is part of my thesis research, conducted under the supervision of Anna van der Meulen at the Leiden Institute of Advanced Computer Science (LIACS).

This study investigates how generative AI use relates to students' sense of belonging and perceived competence within CS programmes. You are invited to participate if you are currently enrolled in a Bachelor's or Master's programme at LIACS.

The survey takes approximately 10-15 minutes to complete. Your responses are anonymous. No identifying information will be collected unless you choose to provide your contact details at the end for a potential follow-up interview. Data will be stored securely and used solely for the purposes of this research.

Participation is entirely voluntary. You may stop at any time without consequence.

If you have any questions about this study, please contact me at s3323609@vuw.leidenuniv.nl.

. By selecting the option below, you confirm that you have read the information above and agree to participate in this study.

I agree and wish to continue

Demographics

Q0. What is your age range?

18-21

22-24

25-29

30+

Q1. What is your gender identity?

Male

Female

Non-binary / third gender

Prefer not to say

Q2. Are you an international student?

Yes

No

Prefer not to say

Q3. Do you have a functional impairment that may affect your studies?

Prefer to not disclose

No

Yes, ADHD

Yes, Autism Spectrum Disorder

Yes, other:

Q4. What is your current programme?

BSc Computer Science

BSc Data Science and AI

BSc Bioinformatics

BSc Computer Science and Economics

MSc Computer Science (all specialisations)

MSc Creative Intelligence & Technology

Q5. What is your current year of study?

Year 1

Year 2

Year 3+

Q5. What is your current year of study?

Year 1

Year 2+

Q6. How did you gain programming experience before starting your current programme? (Select all that apply)

Lessons at secondary school

Code club, workshops, or courses outside of school

Self-taught

Q7. How many years of programming experience did you have before starting your current programme?

No prior experience

Less than 1 year

1-3 years

More than 3 years

Q8. Do you use generative AI tools in your studies?

Yes

No

Generative AI Use

. *The following questions ask about your use of generative AI tools (such as ChatGPT, Gemini, or GitHub Copilot) in the context of your CS courses. Please answer based on your general experience across your studies.*

For each statement, indicate how often it applies to you (1 = Never, 5 = Always).

Q9. I use generative AI for coding assignments

Never

Sometimes

About half the time

Most of the time

Always

Q10. I ask a generative AI to generate a complete solution to a task.

Never

Sometimes

About half the time

Most of the time

Always

Q11. I use generative AI mainly to debug or test my own code.

Never

Sometimes

About half the time

Most of the time

Always

Q12. I rely on generative AI when I feel stuck on a problem.

Never

Sometimes

About half the time

Most of the time

Always

Q13. I discuss AI-generated code with peers before submitting.

Never

Sometimes

About half the time

Most of the time

Always

Q14. I have received formal guidance from my university on AI use.

Yes, during every course

Yes, once during my programme

No, never

. Is there anything else you would like to add about how you use generative AI in your studies? *(optional)*

Perceived Competence

. *The following statements are about how you generally feel about your own abilities within your CS programme, across different courses.*

For each statement, indicate how much you agree (1 = Strongly disagree, 5 = Strongly agree).

Q15. I am confident solving new programming problems on my own.

Strongly disagree
Somewhat disagree
Neither agree nor disagree
Somewhat agree
Strongly agree

Q16. I feel capable of writing clean, well-documented code.

Strongly disagree
Somewhat disagree
Neither agree nor disagree
Somewhat agree
Strongly agree

Q17. I can explain my code to classmates without using AI.

Strongly disagree
Somewhat disagree
Neither agree nor disagree
Somewhat agree
Strongly agree

Q18. I trust my own judgement when evaluating code quality.

Strongly disagree

Somewhat disagree

Neither agree nor disagree

Somewhat agree

Strongly agree

Q19. I feel I am able to meet the challenges of performing well in this programme.

Strongly disagree

Somewhat disagree

Neither agree nor disagree

Somewhat agree

Strongly agree

Imposter-type Feelings

. *The following statements are about how you feel about yourself as a CS student. Please answer based on your general experience within your programme.*

For each statement, indicate how much you agree (1 = Strongly disagree, 5 = Strongly agree).

Q20. I worry that others may discover I am not as competent in CS as they think I am.

Strongly disagree

Somewhat disagree

Neither agree nor disagree

Somewhat agree

Strongly agree

Q21. I often believe my successes in CS are due to luck or good timing rather than my ability.

Strongly disagree

Somewhat disagree

Neither agree nor disagree

Somewhat agree

Strongly agree

Q22. I sometimes feel I have worked my way to my current level in CS without truly earning it.

Strongly disagree

Somewhat disagree

Neither agree nor disagree

Somewhat agree

Strongly agree

Q23. I fear being exposed as less capable than others expect when presenting or discussing my work.

Strongly disagree
Somewhat disagree
Neither agree nor disagree
Somewhat agree
Strongly agree

Q24. I tend to downplay my achievements in CS because I feel they are not fully deserved.

Strongly disagree
Somewhat disagree
Neither agree nor disagree
Somewhat agree
Strongly agree

Q25. When I receive positive feedback on my work, I often think it reflects the evaluator's kindness rather than my own ability.

Strongly disagree
Somewhat disagree
Neither agree nor disagree
Somewhat agree
Strongly agree

Q26. Even when I succeed, I have difficulty believing that I truly earned my achievements in CS.

Strongly disagree

Somewhat disagree

Neither agree nor disagree

Somewhat agree

Strongly agree

Q27. I often feel that other students are more naturally capable in CS than I am, even when my performance is similar.

Strongly disagree

Somewhat disagree

Neither agree nor disagree

Somewhat agree

Strongly agree

. Is there anything else you would like to share about how you sometimes feel as a CS student? *(optional)*

Perceived AI Impact on Programming-Related Skills

. *The following statements are about how you feel AI use has affected your skills and habits in the context of programming and your CS courses.*

For each statement, indicate how much you agree (1 = Strongly disagree, 5 = Strongly agree).

Q28. Using AI has improved my ability to debug code independently.

Strongly disagree

Somewhat disagree

Neither agree nor disagree

Somewhat agree

Strongly agree

Q29. AI use has reduced the amount of collaborative problem-solving I do with peers.

Strongly disagree

Somewhat disagree

Neither agree nor disagree

Somewhat agree

Strongly agree

Q30. I feel less confident discussing technical ideas with others without AI assistance.

Strongly disagree

Somewhat disagree

Neither agree nor disagree

Somewhat agree

Strongly agree

Q31. AI has helped me write more readable and maintainable code.

Strongly disagree

Somewhat disagree

Neither agree nor disagree

Somewhat agree

Strongly agree

Q32. Relying on AI makes me less inclined to seek feedback from instructors or peers.

Strongly disagree

Somewhat disagree

Neither agree nor disagree

Somewhat agree

Strongly agree

Academic Belonging

. The following statements are about how you personally experience your place within your CS programme. These questions touch on feelings that can be quite personal, and there are no right or wrong answers. Please answer honestly based on your general experience across your courses, not one specific course.

For each statement, indicate how much you agree (1 = Strongly disagree, 5 = Strongly agree).

Q33. I feel like a real part of the CS community at this university.

- Strongly disagree
- Somewhat disagree
- Neither agree nor disagree
- Somewhat agree
- Strongly agree

Q34. I feel that my peers and lecturers value my contributions in CS courses.

- Strongly disagree
- Somewhat disagree
- Neither agree nor disagree
- Somewhat agree
- Strongly agree

Q35. The people in my CS programme are friendly towards me.

Strongly disagree

Somewhat disagree

Neither agree nor disagree

Somewhat agree

Strongly agree

Q36. I am comfortable asking for help in CS classes.

Strongly disagree

Somewhat disagree

Neither agree nor disagree

Somewhat agree

Strongly agree

Q37. I feel accepted by my fellow CS students.

Strongly disagree

Somewhat disagree

Neither agree nor disagree

Somewhat agree

Strongly agree

Q38. I feel comfortable being myself when discussing technical topics.

Strongly disagree

Somewhat disagree

Neither agree nor disagree

Somewhat agree

Strongly agree

Q39. I feel that my presence matters within the CS learning environment.

Strongly disagree

Somewhat disagree

Neither agree nor disagree

Somewhat agree

Strongly agree

Q40. I see myself as a CS programmer.

Strongly disagree

Somewhat disagree

Neither agree nor disagree

Somewhat agree

Strongly agree

Q41. I feel I belong in this CS programme.

Strongly disagree

Somewhat disagree

Neither agree nor disagree

Somewhat agree

Strongly agree

. Is there anything else you would like to share about how you experience your place within the CS programme? *(optional)*

After Survey Question

. Would you be willing to participate in a short follow-up interview (approximately 30–45 minutes) about your experiences with generative AI and your sense of belonging in CS? If so, please leave your email address below. Your contact details will be stored separately from your survey responses and will not be linked to your answers.

Interview Guide

Research: Generative AI Use and Sense of Belonging among Computer Science Students

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General Instructions

This interview guide serves as a framework, not a strict script. The order of questions may be adjusted based on the flow of the conversation. If a participant spontaneously raises a topic, there is no need to ask about it again.

Interviews last approximately 30 to 45 minutes. Begin with a brief introduction and close with space for the participant to add anything they feel is missing.

Introduction

Thank the participant for their time and briefly explain:

- What the research is about
- That the interview will be recorded
- That the recording will only be used for transcription and will be deleted afterwards
- That the participant will remain anonymous in all reporting
- That participation is voluntary and that the participant may stop or skip a question at any time

Ask whether the participant has any questions before the interview begins.

Standard opening: "Thank you for taking the time to participate. I am researching how Computer Science students use generative AI and how that relates to how they feel within their programme. The interview will last approximately 30 to 45 minutes. Everything you say will be processed anonymously, the recording will only be used for transcription and will be deleted afterwards. You may stop or skip a question at any time if you prefer. Do you have any questions before we begin?"

Block 1. Background and Warm-up

Introduction: "We'll start with talking about a bit of your background."

Main question 1 Could you tell me a little about yourself, for example what year you are in and which programme you are following?

Follow-up 1a. How far along are you in your programme?

Follow-up 1b. Are you enjoying your programme so far?

Block 2. GenAI Use

Introduction: "We are now going to talk about how you use generative AI in your studies."

Main question 2 Do you use generative AI tools for your studies, and if so, could you tell me a bit about that?

Follow-up 2a. Could you give a concrete example of the last time you used an AI tool for your studies?

Follow-up 2b. For which tasks do you mainly use AI, and for which tasks do you not — for example when coding, debugging, writing, planning, or explaining?

Main question 3 When did you start using AI in your studies?

Follow-up 3a. Was that something you started deliberately, or did it happen gradually — and has the way you use AI changed since then?

Transition: "You mentioned that you use AI for [example from participant]. I am also curious about whether that extends to how you work with others."

Main question 4 Does AI use affect how you collaborate with fellow students?

Follow-up 4a. In what way exactly?

Follow-up 4b. Do you also use AI while collaborating with others, or do you keep that separate?

Block 3. Self-perception, Competence, and Dependency

Introduction: "We are now going to talk about how you assess your own skills as a CS student, and whether the use of AI has any influence on that."

Main question 5 Could you tell me something about how you assess your own programming skills?

- Do you think you are generally good or bad at it?

Follow-up 5a. In which moments do you feel particularly confident or uncertain about that?

Follow-up 5b. Does that differ depending on the type of task, for example coding, debugging, or more theoretical assignments?

Transition: “You mentioned that [assessment of own programming skills]. I am curious whether your use of AI also plays a role in that.”

Main question 6 Does your use of AI affect how competent you feel?

Follow-up 6a. Imagine you are working on an assignment and you use GenAI — how does that affect how good you feel about the assignment?

Follow-up 6b. Do you notice that AI use affects how independent you feel in your studies?

Main question 7 How competent do you feel in situations where you cannot use AI, such as during exams or code reviews?

Follow-up 7a. Do you ever feel that you rely on AI too much?

Block 4. Belonging and Legitimacy

Introduction: "We are now going to talk about how you feel as a student within your programme. I do not only mean academically, but also how you experience your place within it. Maybe you need some time to think about certain questions, but try to say what comes into your mind when it does."

Main question 8 Why did you choose this programme, and does it still match what you expected?

Follow-up 8a. Do you generally feel like you belong in this programme?

- Both academically and socially?

Follow-up 8b. Are there people, situations, or moments that strengthen or weaken that feeling?

Main question 9 Do you feel there is a CS community at LIACS, and do you feel part of it?

Follow-up 9a. Could you explain what makes you feel that way, or not?

Follow-up 9b. *If someone indicates they do not experience a strong community:* Do you feel a need for that, or does it not matter much to you?

Follow-up 9c. Do you spend a lot of time at the university, and do you get along well with your fellow students?

- Is that important to you?

Main question 10 Do you ever feel like you have to prove that you really belong in the programme?

Follow-up 10a. When does that come up most — are there specific situations or moments?

Transition: "We have just talked about how you feel within the programme in general. I am curious whether you connect that to your use of GenAI."

Main question 11 Do you yourself see a connection between how you use AI and how you feel within the programme?

Follow-up 11a. Could you elaborate on that?

Follow-up 11b. *If someone does not see a connection:* Do you think AI use affects how others see you as a CS student, or how you see yourself?

Main question 12 If you can only solve a problem with the help of AI, what does that do to how you feel about yourself as a CS student?

Follow-up 12a. How does that feel in that moment?

Follow-up 12b. Does that change how you look at other students, for example if you feel they use AI less or more than you do?

Main question 13 Earlier we talked about whether you feel you rely on AI too much. Do you think that also affects how you feel within the programme?

Follow-up 13a. Does that feeling of dependency affect how you feel within the programme?

Follow-up 13b. Do you think AI use plays a role in how you feel compared to your fellow students?

Closing

Main question 14 Is there anything we have not discussed that you think is important for this topic?

Closing question How did you find it to talk about this?

Thank the interviewee for their time and participation. Remind them that, should there be any questions or doubts, they can also send an email.

Notes

- Start with concrete questions before moving to more sensitive topics.
- Use neutral phrasing, for example "How does that feel for you?" rather than "Don't you find that difficult?"
- Allow space for silences.
- Ask for examples, not assumptions.
- If a participant spontaneously raises a topic, there is no need to ask about it again.