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Learning with GenAI: A Student-Perspective on the Use of GenAI Tools in
Higher Education

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BACHELOR THESIS

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Abstract

Background: The rapid development of Generative AI (GenAI) tools has introduced new opportunities and challenges in higher education. Although these tools can improve productivity and support learning, their impact on academic integrity and responsible use remains disputed. Existing research often overlooks the student perspective, particularly how they integrate GenAI into their academic workflows.

Aim: This study investigates how Computer Science students at Leiden University use GenAI tools to support academic tasks in their workflows. By examining how these tools are used, how students experience them, and the ethical implications of their use, we seek to inform the responsible and effective integration of GenAI in education.

Method: A single case study design was employed using a mixed-methods approach. Data was collected through 12 semi-structured interviews, a survey with 97 valid responses, and an observation of ChatGPT prompt logs from 2 project groups. Thematic analysis and workflow mapping were used to identify patterns, which were quantitatively validated through survey data.

Results: Students mainly use GenAI to support rather than replace academic work, particularly during later stages of their workflows. Their engagement is shaped by motivations such as productivity, accessibility to support, and adaptation to a changing learning environment. However, concerns about hallucinations, dependency, and academic integrity influence when and how GenAI is used. Students employ a variety of strategies to evaluate and adapt GenAI output, but disclosure of use remains rare and inconsistent.

Conclusion: This study contributes a student-centred perspective on GenAI use in higher education, highlighting both the benefits and risks of integration. Students actively experiment with GenAI in various academic tasks, creating personal strategies to use these tools. However, unreflective use risks compromising learning and integrity, underscoring the need for transparent policies and responsible use frameworks.

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Chapter 1

Introduction

In November 2022, ChatGPT was released to the public. Within weeks, the tool became a global phenomenon. The application grew so fast that it set a record for the fastest growing user base in just two months, with the chatbot estimated to have reached 100 million active monthly users by January 2023 [12]. The introduction of this application catalysed the emergence of numerous other tools and significantly increased public awareness of the concept of generative AI. Students, professionals, and hobbyists alike began experimenting with its capabilities, from writing essays and debugging code to dinner inspirations.

Generative AI (GenAI) tools such as ChatGPT, NotebookLM, and others can generate text, code, images, and more in response to natural language prompts. These tools have quickly transformed the way people search for information, write, code, and learn. For higher education, this marked the beginning of a new era. The accessibility and versatility of these new tools have made them attractive to students seeking support with everything from brainstorming to proofreading. Institutions scramble to update policies and educators debate the ethics of AI-assisted learning. Meanwhile, students are already using these tools, often without clear guidance, in ways that are both creative and controversial.

This thesis takes a student-centred perspective by exploring how Computer Science students at Leiden University are using GenAI tools in practice. By examining how these tools are used, how students experience them, and the ethical implications of their use, this study seeks to inform the responsible and effective integration of GenAI in education.

1.1 Problem statement

Much of the existing research on GenAI in education has evaluated the outcomes of GenAI use in education, institutional responses, theoretical frameworks, or the technical capabilities of the tools themselves. For example, GenAI tools have been shown to improve productivity, writing quality, and programming performance [33, 35, 2]. At the same time, their widespread use has sparked debates around academic integrity, assessment validity, and the role of human cognition in learning. Tsekouras et al. [33] noted that even though GenAI use enhanced surface-level writing quality, it can also undermine deeper cognitive processes such as argumentation and reasoning. Rasul et al. [24] highlighted the risks posed by hallucinations and the current lack of reliable detection tools, which complicate efforts to uphold academic integrity. Similarly, Kosmyna et al. [16] warned against the accumulation of “cognitive debt”, when students rely on GenAI without critically engaging with its output.

Despite these important contributions, the lived experiences of students are often overlooked in the literature. Most studies focus on theoretical or institutional perspectives, leaving a gap in our understanding of how students themselves are adapting to this new technology. More recently, however, scholars have begun to call for research that focuses on the student perspective. Laato et al. [17] and Kim and Lee [14] both emphasise the need for case studies that explore real-world applications of GenAI in educational settings.

This study responds to those calls. It explores how Computer Science students at Leiden University integrate GenAI tools into their academic workflows. These students are not waiting for scholars to tell

them the do's and don't of GenAI use. Instead, they are actively exploring, adapting, and developing their own strategies to use GenAI tools. This study aims to understand those strategies, the motivations behind them, and their implications for learning and academic integrity. Specifically, the goal is to document their patterns of GenAI use and to understand the reasoning behind them. This includes the motivations for choosing GenAI at specific moments, the methods to evaluate its output, and the strategies developed to ensure quality and prevent overreliance.

As Wood and Moss [34] argue, “The success of GenAI integration hinges on identifying and implementing best practices that not only enhance educational outcomes but also safeguard against pitfalls such as academic dishonesty and an overreliance on AI for tasks requiring critical thinking.” This quote underscores the need to balance innovation with integrity. Although GenAI tools offer powerful opportunities to support learning, their effectiveness ultimately depends on how thoughtfully they are used. This study contributes to this effort by mapping student workflows, analysing engagement strategies, and exploring disclosure practices. By focusing on the student perspective, this research helps identify not only where GenAI adds value, but also where it may risk undermining essential learning processes. Ultimately, these insights are instrumental to developing responsible AI practices.

1.2 Research questions

To achieve this aim, the main research question guiding this study was:

How is Generative AI used by Computer Science students to support academic work?

To explore this overarching question, the following sub-questions were formulated:

RQ.1 How do CS students use GenAI tools at different stages of their academic workflows?

RQ.2 How do CS students experience using GenAI tools?

RQ.3 How do student choices about disclosure of GenAI use affect academic integrity?

These questions are designed to uncover not just what students do, but also why they do it and how their choices shape the learning process. To answer these questions, this study uses a single case study design. The focus of the case study is on Computer Science students at Leiden University. A mixed-methods approach was used to capture both qualitative and quantitative insights. Data was collected through semi-structured interviews, a survey, and prompt logs from two student project groups. This triangulation of methods allows for a rich, contextualised understanding of GenAI use in practice.

1.3 Overview of the thesis

This thesis is structured as follows. Chapter 2 reviews the relevant literature, including definitions of GenAI, its educational applications, and its implications for academic integrity. Chapter 3 outlines the research methodology, detailing the mixed-methods design, data collection procedures, and analytical methods. Chapter 4 presents the results of the study, organised by academic task and cognitive level. Chapter 5 interprets the findings in relation to the existing literature, highlights limitations, and proposes directions for future research. The thesis concludes with a summary of key insights and their implications for higher education in Chapter 6.

Chapter 2

Background and related work

The rapid development of GenAI has introduced both opportunities and challenges. This chapter includes existing research on the capabilities and limitations of GenAI, its impact on learning and cognitive development, and institutional perspectives on its permissible use in academic settings.

2.1 Generative AI

GenAI’s capabilities continue to evolve, capturing widespread public and academic attention, especially after the release of ChatGPT in late 2022 [32]. Despite its popularity, the term “GenAI” remains loosely defined and is used mainly in public and interdisciplinary contexts [26, 23]. Peñalvo and Ingelmo [23] define GenAI as “the production of previously unseen synthetic content, in any form, and to support any task, through generative modelling.” This definition captures the broad scope of GenAI applications, from text and image generation to code creation and audio production. However, it also underscores the need to narrow the scope when studying GenAI in specific contexts such as for this research. Therefore, the focus in this study is on accessible tools that students commonly use in academic settings. These include large language models and similar systems that allow users to generate content using natural language prompts. GenAI tools are thus defined as tools such as ChatGPT, NotebookLM, or similar applications that can independently generate content such as text, code, audio, or images.

The large language models used in GenAI are capable of producing this variety of outputs based on user input, which is referred to as a prompt [15]. The process of writing these prompts, known as prompt engineering, has become a skill to effectively interact with GenAI tools. Prompt engineering involves the creation and refinement of specific inputs for GenAI models to achieve high-quality, relevant, and accurate responses from the model Knoth et al. [15]. Furthermore, one of the risks associated with GenAI is its tendency to produce hallucinations, outputs that are factually incorrect, misleading or nonsensical. To mitigate this, Knoth et al. [15] and Fui-Hoon Nah et al. [10] argue that well-structured prompts play a vital role in reducing hallucinations and bias in GenAI output. This view is supported by Kosmyna et al. [16] and Wood and Moss [34], who emphasise the importance of intentional and reflective engagement with GenAI tools. Hence, prompt engineering is a crucial component in utilising GenAI effectively.

Various prompting methodologies have been proposed to guide users in structuring their interactions with GenAI. These include zero-shot prompting, where the model is given a task without examples; few-shot prompting, which involves providing a small number of examples to guide the model; and chain-of-thought prompting, which encourages the model to reason through incremental steps before arriving at a final answer Knoth et al. [15]. In addition, Eager and Brunton [6] recommended six components that should be included in written prompts to improve clarity and alignment: verb, focus, context, focus and condition, alignment, and constraints and limitations. Similarly, Lee and Palmer [18] propose a pragmatic list that synthesises multiple prompting strategies into seven actionable strategies: 1) define the AI’s role, 2) provide background context, 3) define objectives, 4) set parameters, 5) be precise, 6) specify the desired output format, and 7) iteratively refine the prompt based on the models response.

2.2 The impact of GenAI on education

As GenAI tools become increasingly accessible and capable, their integration into educational contexts has sparked both enthusiasm and concern. Understanding how these tools are used in learning environments is essential to evaluating their impact on student development. Lodge et al. [19] propose a research agenda that emphasises the need for evidence-based guidance on how GenAI affects learning, teaching, and institutional leadership in higher education.

One of the primary challenges in preparing students for a GenAI-integrated world is to ensure that they develop the skills necessary to work effectively alongside these technologies. However, before such skills can be meaningfully developed, students and educators alike must first understand how GenAI systems function [19]. This includes examining how these tools generate content, how they represent knowledge, and what implications their use has for educational practices. Resources such as the UNESCO guide on ChatGPT in education [28] offer accessible introductions to these technologies, particularly for those without technical backgrounds. Lodge et al. [19] also highlight the importance of Explainable AI, which can help educators and students critically assess AI-generated output.

2.2.1 Academic achievement

To meaningfully assess the impact of GenAI on education, we must clarify what “learning” means. To do this, we must look beyond traditional metrics, such as test scores or grades. Sun and Zhou [30] use the term “academic achievement” as a measure to evaluate the effectiveness of GenAI in supporting college students’ learning. The study defines academic achievement as “the extent to which students acquire and apply valuable knowledge, skills, and emotional competencies throughout their educational experience”. This broader definition includes both cognitive and non-cognitive dimensions. The cognitive domain includes competencies such as mastery of subject knowledge, critical thinking, and problem solving, while the non-cognitive domain involves factors like motivation, self-efficacy, interest, and attitudes. By adopting this perspective, researchers can more accurately evaluate how GenAI tools influence student development across various aspects of learning.

Several studies have examined the role that GenAI can play in supporting academic achievement. Yusuf et al. [37] and Sabzalieva and Valentini [28] discuss GenAI’s potential as a personalised learning tool, serving roles such as a “personal tutor,” a “study buddy,” and a “motivator,” by providing immediate feedback and challenging tasks tailored to students’ learning paces and needs. Studies demonstrate GenAI’s effectiveness, particularly in independent learning scenarios and lower cognitive levels, aiding information recall and concept understanding [30, 8]. In addition, GenAI is theorised to enhance specialised training and decision making by simulating real-world scenarios [37]. It can serve as a “dynamic assessor” to assess knowledge levels, or a “Socratic opponent” to promote critical thinking [28]. However, while aiding writing quality, GenAI may undermine deeper cognitive skills like argumentation [33]. Furthermore, GenAI can facilitate data analysis, allowing students to practice to improve complex analytical skills [37, 28]. The tools show varied effectiveness across disciplines, with the most significant impact in humanities and the least in natural sciences [30, 9]. Finally, as an interdisciplinary tool, GenAI functions as a “writing assistant” and “productivity tool,” with roles expanding to idea generation and collaboration. Its integration into education is still developing, requiring thoughtful adaptation for different disciplines [27].

2.3 Academic integrity

While GenAI presents valuable learning opportunities for students, it also raises concerns about academic integrity. Academic integrity is a foundational principle in higher education and is defined by a commitment to six core values: honesty, trust, fairness, respect, responsibility, and courage [13]. Violations of these values can take various forms, such as plagiarism, cheating, data falsification, and inappropriate collaboration [24, 25]. When students or scholars engage in academic dishonesty, they compromise the validity of assessments and undermine the larger goals of academia [24].

2.3.1 Challenges associated with the use of GenAI tools

The improved quality of GenAI output has introduced new concerns about how students might misuse these tools. Submitting generated content as original work violates the core principles of academic

integrity [7]. However, as the quality of GenAI output improves, it becomes increasingly difficult to determine whether a student’s submitted work is their own or the result of GenAI assistance. Cotton et al. [4] illustrated ChatGPT’s ability to generate academic writing by submitting AI-generated work to an academic journal, together with a discussion on its impact on academic integrity. Such examples underscore the growing possibility for students to use GenAI to produce essays or assignments that are then submitted without appropriate attribution.

Another challenge associated with GenAI tools is the possibility of hallucinations, where the tool produces content that is factually incorrect, incomplete, or entirely fabricated [24]. These hallucinations can appear highly convincing, making them difficult for users to detect if they do not have previous knowledge of the subject. This presents a risk to academia, as students may unintentionally include these hallucinations in their work. This issue highlights the importance of critical thinking skills in evaluating the credibility of the information GenAI tools generate [24].

Finally, detecting the use of GenAI tools in academic work presents a significant challenge, as current detection technologies are still in their infancy and often unreliable. Tools such as GPTZero and other GenAI-detectors struggle with false positives and false negatives [1]. This ambiguity makes it difficult for educators to confidently determine whether academic dishonesty has occurred. As a result, it is difficult to enforce practices that align with academic integrity.

2.3.2 Responsible GenAI use

According to Wood and Moss [34], the responsible use of GenAI is guided by the principles of fairness, transparency, accountability, and the well-being of individuals and society. In academia, this includes acknowledging GenAI-assisted contributions appropriately, understanding the limitations of GenAI output, including potential inaccuracies or hallucinations, and avoiding uncritical reproduction of AI-generated content. However, a standardised and responsible way of acknowledging the use of GenAI tools has not yet been fully developed across academia. Although some researchers have gone so far as to list tools like ChatGPT as co-authors, leading academic publishers such as Nature and Science have explicitly rejected this practice, arguing that LLMs cannot fulfil authorship responsibilities, such as accountability for content or ethical decision-making [7, 1].

Bozkurt [1] advocates for a more refined method of documenting the use of GenAI tools in the form of a final human approval statement. The statement should recognise and evaluate the involvement of GenAI, including any iterative editing stages. The study suggests the *Academic Integrity and Transparency in AI-assisted Research and Specification* (aiTARAS) Framework, designed to guide the ethical disclosure of AI use in academic writing. This framework reinforces the principle that ultimate accountability for content remains with the human author.

The range of methods to acknowledge the use of GenAI can be observed in universities. Moorhouse et al. [20] reviewed guidelines from top-ranking universities and found various approaches to acknowledge GenAI use. Recommended practices include citing the specific AI tool used and access date, documenting the process and prompts used, and providing an appendix detailing how GenAI outputs were incorporated into the work. Some institutions suggest using different citation formats, depending on the nature of use, such as ideation, drafting, or editing [20]. As universities adapt to this new technology, they emphasise critical thinking as an essential skill for students to develop when working with GenAI tools [24, 20]. This focus on critical evaluation helps students assess the reliability and accuracy of the generated content rather than accepting it without further thought. Another important factor in responsible use is communication between educators and students. The analysed guidelines encourage instructors to have open discussions about what GenAI tools can and cannot do, highlighting aspects of assignments that cannot be outsourced. Setting clear expectations is equally crucial, and instructors must establish explicit parameters regarding permissible uses, required disclosure methods, and the importance of originality and intellectual participation in the learning process [20].

2.4 GenAI collaboration

To better understand how students interact with GenAI tools, it is helpful to consider theoretical frameworks that describe the cognitive and functional dimensions of learning. Although this study does not apply these frameworks directly in its analysis, they offer another perspective on the role of GenAI in education.

The AI-ICE framework offers a lens through which collaboration between students and GenAI can be analysed, with a particular focus on the cognitive effort students use during these interactions [34]. This framework builds on the assertion that while GenAI systems can augment learning, humans should remain decision makers. Effective collaboration between students and AI is achieved when the combined effort leads to better outcomes than either could independently produce.

The framework, developed by Wood and Moss [34], synthesizes two conceptual models: the ICE Model (Ideas, Connections, Extensions) and the three paradigms of AI in education. The ICE Model outlines three progressive stages of cognitive engagement, from acquiring foundational knowledge (Ideas), to analysing and connecting information (Connections), to creatively applying knowledge in new contexts (Extensions) [36]. These stages are complemented by three paradigms of AI integration in education as proposed by Ouyang and Jiao [22]. The three paradigms represent different roles and relationships between learners and AI technologies. In AI-directed learning, the GenAI system leads the learning process and is the student mainly receiving information. In AI-supported learning, the AI acts as a collaborative partner, enhancing the learning experience through interaction and feedback. In AI-empowered learning, the student takes the lead by using AI tools to support independent inquiry and creative problem solving.

Paradigm	Level	Characteristics
AI-Directed	Ideas	Introduction to basic AI tools and functionalities; Focus on understanding AI in learning processes; Basic competency in using and understanding AI outputs; Emphasis on responsible AI use; an awareness of limitations and biases
AI-Supported	Connections	Active use of AI tools in collaborative settings; Integration of AI insights into learning strategies; Advanced competence in manipulating AI tools for educational outcomes; Critical evaluation of AI's ethical implications in education.
AI-Empowered	Extensions	Leadership in applying AI creatively and comprehensively; Effective use and adaptation of AI tools, including development of new applications; Deep engagement with ethical considerations of AI, including bias, privacy and equitable access.

Table 2.1: AI-ICE Framework, table by Wood and Moss [34]

Together, these models form the AI-ICE framework, consisting of three dimensions: AI-Directed/Ideas, AI-Supported/Connections, and AI-Empowered/Extensions [34]. The framework explicitly excludes the passive use of GenAI, as this would contradict its goal of promoting cognitive development. Instead, it assumes that students should be actively involved in shaping their learning experiences when using GenAI tools. In their study, Wood and Moss [34] applied the AI-ICE Framework to evaluate students' cognitive engagement with GenAI in a master's-level instructional design course. The course incorporated GenAI tools through practical, reflective activities designed to foster ethical awareness and critical thinking. The study found that most students were classified at the AI-Directed/Ideas level, with a few reaching the AI-Supported/Connections tier.

Chapter 3

Methodology

This chapter outlines the methodological approach used to investigate how Computer Science students at Leiden University integrate GenAI tools into their academic workflow. The following sections will describe the research design, data collection methods, and analytical methods used to interpret the data.

3.1 Research Design

This study adopts a single case study design, focusing on Computer Science students at Leiden University. This design was chosen because it allows for an in-depth exploration of student behaviour in a real-world context. The aim is to examine how students use GenAI tools in their academic workflows. Using a case study approach, we conducted a detailed exploration of student behaviours, motivations, and perceptions within a particular institutional and disciplinary context. Although this method limits the broad applicability of results to other institutions or disciplines, it provides deep, context-specific insights into the use of GenAI in higher education.

To achieve this, the study employs a mixed-methods approach, combining semi-structured interviews, a survey, and analysis of ChatGPT prompt logs. Each method contributes different strengths to the study. The semi-structured interviews provide detailed qualitative insights into student reasoning and decision-making, but were limited in generalisability. The survey offers broader quantitative validation of emerging patterns. The ChatGPT prompt logs add observational data on actual tool use. Together, these methods enable methodological triangulation, enhancing the validity of the findings through cross-verification across data sources. This approach was chosen for its potential to first uncover in-depth, contextual insights, and then validate those patterns across a broader population.

3.2 Data Collection Methods

To capture the complexity of GenAI use in academic contexts, three complementary data collection methods were employed. The following sections will describe how data was collected through interviews, a survey, and ChatGPT prompt logs.

3.2.1 Semi-structured interviews

The qualitative foundation of the study was built on semi-structured interviews. A total of 12 students enrolled in Computer Science-related programmes at Leiden University participated in these interviews. The sample was selected to represent a range of academic years and specialisations, Table 4.1 provides a demographic overview. All interviews were conducted in Dutch, the participants' native language, and lasted approximately one hour. The interviews were conducted in May 2025. The interview guide (Appendix A) was designed to elicit detailed accounts of GenAI use by students in the academic tasks of writing assignments, programming, and exam preparation. The questions also explored the students' perceptions of the usefulness, reliability, and ethical implications of GenAI. With informed consent, the interviews were recorded and transcribed verbatim. Anonymity was maintained throughout the process.

We included both GenAI tool users and non-users in our analysis. This inclusion was valuable because understanding why some students choose not to use GenAI tools provided insight into perceived limitations, ethical concerns, or learning preferences. The interview guide was therefore crafted to cover diverse experiences, including selective or non-use. When students reported not using GenAI for certain tasks or at all, their usual workflow was still discussed to understand their choices. This method enabled comparisons between workflows with and without GenAI. By including these views, the study avoids bias towards early adopters of GenAI tools and supports a balanced general understanding of student decision making [5]. For interviews J, K, and L, the participants were shown the consolidated workflow diagrams developed from previous interviews. Their feedback and proposed adaptations were incorporated into the final versions of the workflows, allowing iterative refinement and validation of the task sequences.

All participants were informed about the purpose of the study and their rights, including the right to withdraw at any time. Consent was obtained prior to recording the interviews. Data were anonymised during transcription and stored securely. The study complies with the ethical guidelines of Leiden University and does not involve sensitive personal data.

3.2.2 Survey

To complement the qualitative insights and validate emerging patterns, a survey was distributed among students in the same programmes at Leiden University. The survey was designed to quantify the preliminary results of the semi-structured interviews. The survey was posted on Brightspace, Leiden University’s digital learning environment, and distributed via group chats. Survey responses were collected in the month of June 2025. In addition, some students were asked to complete the survey at an exam location from the university. The survey was open to bachelor’s and master’s students. Participation was voluntary and anonymous. The survey consisted of 14 questions and took approximately 5-10 minutes to complete. The survey was divided into five thematic blocks, 1) background information, 2) assignment workflow (combining written and programming assignments), 3) exam preparation workflow, 4) attitudes and motivations, and 5) engagement and disclosure. The questions all used multiple-choice or Likert scales, with an exception for the final two questions. These two questions on disclosure used a multiple selection which allowed respondents to fill in an ‘other’ option. The complete survey questions are included in Appendix D.

The survey combined written and programming assignments into a single workflow. This decision was based on preliminary interview findings that revealed an overlap in the way students approached these assignments. Merging the workflows also helped reduce survey fatigue, resulting in a higher completion rate among respondents. Similarly, the exam preparation process was simplified to achieve the same goal. The survey workflows included the following tasks:

Assignment workflow

1. Understand the assignment requirements (for example, by reading the brief, reviewing provided files, or deciding a scope)
2. Plan the structure or approach (for example, by writing pseudocode or breaking down tasks to be done)
3. Consult resources or documentation (for example, by looking up examples)
4. Write or implement the main content
5. Test or review my work (for example, by checking for errors or unclear parts)
6. Revise or resolve issues (for example, by debugging or improving structure and flow)
7. Add the final touches (for example, by cleaning up formatting, visuals or spelling)
8. Check my work for correctness and originality (for example, by verifying requirements are met, or performing a plagiarism scan)

Exam preparation workflow

1. Identify the exam topics (for example by checking the syllabus or past exams)
2. Make a study plan (for example by creating a schedule that covers all topics in time)
3. Review the course material (for example by going through slides, notes, and assignments)

4. Consult additional resources (for example by watching videos or googling to understand tough topics)
5. Summarise and create study aids (for example by making summaries, glossaries, or flash-cards)
6. Memorise the material (for example by using repetition or active recall techniques)
7. Practice with problems and mock exams
8. Review and reinforce weak areas (for example by practising on additional material)
9. Do a final review before the exam (for example by going over key points and clearing up any last doubts)

The design of the survey for Q8, Q9 and Q11 on motivation was informed by the HEPI 2025 Student Generative AI Survey [9]. In addition, the survey was shaped by preliminary findings from the semi-structured interviews conducted earlier in the study. Although the complete thematic analysis had not yet been completed at the time of survey construction, early patterns, particularly around motivation and engagement, closely mirrored those reported in the HEPI study.

3.2.3 ChatGPT prompt logs

In addition to interviews and survey responses, this study incorporated a third data source: observed GenAI use. This method involved the analysis of ChatGPT threads and logs that motivate the prompts submitted by the students as part of a group project in the course *Integration: Business-IT-Alignment*. These threads provided observational data on student interactions with GenAI tools, without relying on self-reports.

Two groups agreed to allow their GenAI chat history to be used for research purposes. The students worked on a project in which they were tasked with writing an advisory report for a fictional company, focusing on Business & IT Alignment. The assignment was divided into three phases: defining the scope and strategy, performing a capability assessment across technology, people, and processes, and formulating an actionable implementation plan. Throughout the project, students applied theoretical models, practised analytical thinking, and presented their findings.

The course required the students to provide chat histories and log their use of GenAI tools in a standardised format. This included specifying who in the team group used the tool, the purpose of the prompt, the exact prompt used, how the generated input was incorporated into the report (or why it was not used) and a critical evaluation of the output’s usefulness. The translated format of the prompt log is presented in Table 3.1. To contextualise these prompts, interviews were conducted with group members. The interview guide for the semi-structured interviews was adapted for this purpose and is included in Appendix B. The guide was designed to clarify intentions, assess strategies, and evaluate perceived usefulness.

3.3 Data Analysis

The data collected was analysed using a combination of qualitative and quantitative techniques. The following sections will describe how the data was analysed through thematic analysis and descriptive statistics.

3.3.1 Semi-structured interviews

To support the analysis, individual workflow diagrams were constructed for each participant based on their descriptions of how they approached writing assignments, programming tasks, and exam preparation. These diagrams were validated during the interviews and then consolidated into comprehensive workflow diagrams for each academic activity. This process enabled a comparison between participants and helped identify where and how GenAI tools were integrated or excluded from student workflows.

The interview data was analysed using inductive thematic analysis to uncover patterns in how students use GenAI tools in their academic work. The process started with open coding. First, each transcript was read line by line to identify meaningful segments related to the workflows, motivations, and experiences

Who	Purpose	Prompt	How the input was processed/used in the report	Evaluation
Who in your group performed this task	Here you explain the purpose for which you created this prompt. If you have used multiple prompts for the same purpose, you may copy the purpose.	Here you copy the prompt you used.	Here you explain how you processed or used the input in your report. If you have used multiple prompts for the same purpose, indicate “Not used” for the prompts you did not use in the report, and explain in the next column why the output from GenAI did not meet your expectations.	Here you explain your evaluation of the output from GenAI. For example, you clarify whether you found the output useful and why, or whether it was partially useful and why, or not useful at all and why.

Table 3.1: Translated logbook format of *Integration: Business & IT-Alignment* assignment

of students with GenAI. These initial codes captured specific actions (e.g., “used GenAI to debug code”), motivations (e.g., “GenAI saves me time”), and reflections (e.g., “I learn less using GenAI”). In the next phase, similar codes were grouped into broader themes, such as “GenAI use descriptions,” “prompt engineering strategies,” and “concerns about academic integrity.” This iterative process allowed themes to emerge from the data.

3.3.2 Survey

The survey included two sets of questions (Q4-Q5 and Q6-Q7) designed to evaluate the different workflows. Questions Q4-Q5 focused on the combined workflow for written and programming assignments, and Q6-Q7 addressed the exam preparation workflow. The use of Qualtrics’ Loop & Merge feature allowed the survey to present questions in sequences corresponding to different workflow steps. Participants first indicated how frequently they followed each step (Q4, Q6), and then if they employed generative AI tools during these steps (Q5, Q7). To ensure that only meaningful data was included, the responses were screened for completeness and validity. If a response ended in the demographic section or first workflow set, it was entirely excluded to maintain the integrity of the data. Partial responses that did not cover the entire second set of workflows were adjusted by marking all questions of the incomplete set as missing (NaN) to avoid skewing the analysis of usage patterns across the full set of workflow steps.

To assess the rate at which students use GenAI tools for certain tasks, students were first asked to indicate how often they performed a task in their workflow and then asked how often they used GenAI for that task. Participants were asked to answer these questions on a five-point Likert scale. The results were analysed using a ranking method as described by Serban et al. [29] and Offerman et al. [21]. For each task, the percentage of respondents who reported at least high adoption (answering “always”), at least medium adoption (answering “always” or “most of the time”) and at least low adoption (answering “always”, “most of the time”, or “about half of the time”) were calculated. These percentages were independently ranked across all tasks using the average ranking method, where the tied values share the average of their rank positions. We then calculated the mean of the three rank values (high, medium, and low adoption) to produce an overall average rank for each task. The tasks were sorted according to this average, and lower scores indicated a higher overall adoption. This approach allowed for a systematic comparison of different adoption rates across different academic tasks. The remaining survey data was analysed descriptively. For each question, responses were summarised in tables showing the count and frequency of each answer option.

3.3.3 ChatGPT prompt logs

The analysis of the prompt logs was conducted qualitatively to observe how students interacted with GenAI in practice. Each prompt was coded and mapped to tasks of the writing assignment workflow. In addition, the prompts were coded for elements of prompt engineering. These elements were based on the strategies described in the interviews. Follow-up interviews with group members provided further context and enabled a comparison between observed and reported behaviours.

Chapter 4

Results

This chapter presents the findings of the mixed-method study, combining insights from semi-structured interviews, survey responses, and observed GenAI use. The aim is to present the different ways in which Computer Science students at Leiden University use GenAI tools in their academic work. The results are structured to reflect the research questions and methodological design introduced in earlier chapters, with a focus on the academic workflows that students follow and the ways in which they engage with GenAI tools.

The chapter begins with an outline of the demographic characteristics of the participants, providing a context for interpreting the results. The demographic section covers participants' backgrounds and considerations for using GenAI. Next, we explore how students integrate GenAI tools into their academic workflows, distinguishing between written and programming assignments, and the exam preparation process. These sections combine qualitative insights from interviews with quantitative validation from the survey, and are supported by observed GenAI use at a second-year course assignment. Following this, the focus shifts to how students experience using GenAI tools. This includes the strategies they employ to ensure quality and reliability, and their reflections on the impact of GenAI on their learning. The final section examines how students disclose their use of GenAI in academic work and the factors that influence these decisions.

4.1 Participants of the study

This section introduces the participants whose data form the basis of this study. It includes students who participated in the interviews, those who completed the survey, and two project groups whose use of GenAI was observed in a course setting. Together, these groups provide a rich understanding of how GenAI tools are used in practice. This section details the participants' study programme and year, GenAI use outside academia, comfort and familiarity, and their motivations and concerns that shape their experience with GenAI tools. These factors were selected because they offer a foundation for interpreting how and why students interact with GenAI tools the way they do.

4.1.1 Participant backgrounds

Interview data Twelve students participated in the semi-structured interviews, representing a range of Computer Science-related programmes and academic years at Leiden University. Table 4.1 provides an overview of the background of their study, self-reported comfort with GenAI and use of the tool beyond academics. The interview sample included students from the programmes BSc Data Science and Artificial Intelligence, BSc Computer Science, BSc Computer Science & Economics, MSc ICT in Business and the Public Sector, and BSc Computer Science & Mathematics. The majority of the students were at least in their third year of study or higher.

In addition to programme and year, students reported varying levels of GenAI use outside of academic contexts. Some students described a state of almost daily integration, where GenAI tools had become a default assistant for everyday tasks such as cooking, fitness planning, quick fact-checking, or even replacing Google entirely. Others reported occasional use, turning to GenAI for specific needs like travel

Student	Programme	Year	Usage outside academics	Comfort
A	BSc Data Science and Artificial Intelligence	BSc 3rd Year	Occasional use	High
B	BSc Computer Science	MSc 3rd Year	Daily integration	Moderate
C	BSc Data Science and Artificial Intelligence	BSc 3rd Year	Occasional use	Moderate
D	BSc Computer Science	BSc 4th Year	Occasional use	High
E	BSc Data Science and Artificial Intelligence	BSc 1st Year	Daily integration	High
F	BSc Computer Science	BSc 3rd Year	No use	Low
G	MSc ICT in Business and the Public Sector	MSc 1st Year	Daily integration	High
H	BSc Computer Science & Economics	BSc 2nd Year	No use	Low
I	BSc Data Science and Artificial Intelligence	BSc 3rd Year	Daily integration	High
J	MSc ICT in Business and the Public Sector	MSc 1st Year	Daily integration	High
K	BSc Computer Science & Mathematics	BSc 6th Year	No use	Low
L	BSc Computer Science & Economics	BSc 3rd Year	Daily integration	High

Table 4.1: Demographic overview of interview participants (N = 12, interviews)

planning, creative projects, or casual experimentation, but without incorporating it into their daily routines. A smaller group of students indicated no use of GenAI outside of their studies, either due to lack of interest, perceived irrelevance, or limited experience.

Finally, students expressed varying levels of comfort with GenAI tools, which can be grouped into three broad categories. A group of students reported feeling very comfortable, often describing themselves as confident users who had developed routines or strategies for interacting with GenAI effectively. These students typically used the tools frequently. Others fell into a category of moderate comfort, where they felt generally capable but still cautious. Some shared sometimes being unsure about how to best use the tools or when to trust the output. Finally, a smaller group expressed low comfort, either due to limited experience, uncertainty about the tools’ reliability, or a lack of confidence in their own ability to use them effectively.

Survey data A total of N = 119 survey responses were collected. After filtering, 90 responses were identified as complete and 7 additional responses were considered valid for analysis. Specifically, 18 responses were excluded for ending during the first workflow block, and 5 responses had their second block data removed due to early termination. This approach ensured that the dataset only included respondents who had engaged meaningfully with the full set of questions per workflow, allowing for reliable comparisons between the workflow steps. The survey sample includes both bachelor’s and master’s students, with the majority enrolled in the bachelor’s Data Science and Artificial Intelligence programme. Table 4.2 presents the cross-tabulation of study programmes and the year of study.

Current Study Programme	1st year	2nd year	3rd year	4th year or higher	1st year master’s	2nd year master’s	Total
BSc Computer Science	4	8	6	7	0	0	25
BSc Data Science and Artificial Intelligence	15	13	8	3	0	1	40
BSc Computer Science and Economics	1	2	7	0	0	0	10
BSc Computer Science and Mathematics	0	0	2	2	0	0	4
MSc Computer Science	0	1	0	0	8	5	13
MSc ICT in Business and the Public Sector	0	0	0	0	0	4	4
Total	20	24	23	12	8	10	97

Table 4.2: Cross-tabulation of study programme and year of study (N = 97, survey)

The respondents also reported their familiarity with GenAI tools. As shown in Table 4.3, most of the respondents considered themselves “somewhat familiar” (44.33%) or “very familiar” (36.08%), indicating a generally high level of exposure to these tools. In contrast, fewer respondents reported being “neutral” (11.34%), “somewhat unfamiliar” (4%), or “very unfamiliar” (4.12%).

Familiarity level with GenAI	Count	Percentage
Very familiar	35	36.08%
Somewhat familiar	34	44.33%
Neutral	11	11.34%
Somewhat unfamiliar	4	4.12%
Very unfamiliar	4	4.12%

Table 4.3: Student familiarity with GenAI tools (N = 97, survey)

Prompt log data In addition to interviews and survey responses, this study included the observed use of GenAI of two student project groups (Group A and Group B) enrolled in the course *Integration: Business-IT Alignment*. These groups submitted ChatGPT prompt logs as part of a project, providing an opportunity to analyse GenAI interactions in an academic setting. The logs documented who used the tool, the purpose of each prompt, the exact prompt used, how the output was processed, and an evaluation of its usefulness.

Groups A and B used GenAI with different intensities. Group A recorded a total of 135 prompts. In contrast, Group B documented 10 prompts in their log. Regarding this difference, a group member of Group B commented: “I have used [GenAI] the most and the rest not so much or not at all. No, [this was not a conscious choice as a group], it was just, if you use it, do your thing but make sure to fill [the log] in nicely.” Both groups used the premium version of ChatGPT (version 4), and their logs were contextualised with interviews.

4.1.2 Student considerations around GenAI use

This section explores the motivations and concerns that students expressed about their use of generative AI. Thematic analysis of the interviews revealed four motivational themes for use: support and accessibility of GenAI, productivity, adaptation to an evolving learning environment, and improvement of GenAI skills. These themes reflect how students perceive the role of GenAI in their studies. To complement these qualitative insights, survey data were used to quantify the prevalence of specific motivations in a larger sample. The survey questions on motivation were adapted from the 2025 HEPI Student Generative AI Survey [9]. These questions were selected because they closely aligned with the preliminary patterns emerging from early interviews. In addition to the reasons for using GenAI, the section also examines why some students choose not to use these tools at certain times or at all. Thematic analysis identified concerns related to tool limitations, learning strategies, and academic integrity. These themes are also followed by survey-based quantification to assess how widespread these concerns are among the broader student population. The subsection begins by presenting the thematic codes for both the motivations and concerns regarding the use of GenAI. Following this, the survey results are presented in a similar order.

Interview data. Table 4.4 presents the thematic codes explaining the students’ reasons for using GenAI tools, with frequency showing how many students mentioned each reason. The codes are grouped into four subthemes: productivity, support and accessibility, adapting to a changing learning environment, and improving GenAI skills.

All twelve students mentioned productivity gains from using GenAI tools. This subtheme reflects how students use GenAI tools to reduce the time and effort required to complete academic tasks or to improve the quality of their work. Ten students reported using GenAI to save time, often describing it as a faster way to get explanations or complete tasks. Several students highlighted its usefulness in debugging or problem-solving. As student F shared, “Sometimes you’ve been searching for hours and it turns out to be a tiny mistake, like using an equals sign instead of a less-than sign. GenAI can find that in a minute. For that kind of thing, it’s perfect.” Eight students used GenAI to avoid repetitive or trivial work, particularly when tasks were perceived as time consuming but not cognitively demanding. Seven students used GenAI to reduce the effort required to complete work, most described this motivation as making work “easier” for themselves. This approach resembles a form of outsourcing, in which students delegate certain aspects of their tasks to GenAI. In addition, five students used GenAI to complete tasks that they simply did not want to do. For example, students expressed disinterest in plotting graphs or writing reports for programming assignments. Furthermore, nine students used GenAI to improve the

Subtheme and codes	Frequency
Productivity	12
To save me time	10
To avoid repetitive or trivial work	8
To improve the quality of my work	9
To reduce the effort required to complete work	7
Using GenAI as a starting point or “kickstarter”	5
GenAI to complete work I do not want to do	5
Support and accessibility	11
To get personalised support	9
GenAI as a sparring partner	5
To get support outside of traditional study hours	5
To get instant support	3
I feel unable to keep up without GenAI	3
Adapting to an evolving learning environment	10
To replace traditional tools and methods	8
Because other students use GenAI	3
To improve my GenAI skills	1

Table 4.4: Thematic codes for student motivations to use GenAI tools (N = 12, interviews)

quality of their work, particularly for grammar, structure, or clarity. The students describe using a tool to point out areas of improvement or to refine sentence phrasing. In addition to enhancing the quality of their work, students also used the tool to help kickstart their tasks. Five students used GenAI as a starting point when they did not know how to begin a task. For example, student B described asking for a step-by-step plan to avoid feeling overwhelmed by a complex assignment.

All but one student mentioned how they wanted to use GenAI tools for its support and accessibility. This theme covers how students use GenAI tools to access academic support that is flexible, immediate, and tailored to their individual needs. Nine students described using GenAI to receive personalised support. They valued the ability to ask follow-up questions, request analogies, or receive explanations in simpler terms. For these students, GenAI tools provide answers adapted to the specific context of a student’s problem. As student J explained, “No one has exactly the same problem that you have, and I think that ChatGPT is a lot more flexible when it comes to personal problems you have.” In addition, three students highlighted the value of instant support, especially when working under time pressure. Beyond delivering quick answers, five students appreciated how GenAI tools extend support beyond traditional study hours. Student C illustrated this by comparing the tool with a professor or TA, saying that it helped answer last-minute questions they had not thought to ask earlier. Additionally, five students described using GenAI as a sparring partner. They used the tool to test ideas, refine arguments, or get a second opinion. Notably, three students expressed that they felt unable to keep up academically without GenAI assistance. Student B shared a particularly compelling example: after failing all courses in one semester, they subsequently passed them all with GenAI’s help to better understand the course material.

The third theme touches on how students are affected by the changing learning environment around them, and ten students touched on this. Eight students reported replacing traditional practices with GenAI. The tool most commonly described to be replaced by GenAI is Google. Students often explained their new way of searching as “Google, but better”. Students appreciate the way the tools provide faster and more aggregated answers. Student D noted, “First we used to Google and rely on Stack Overflow. Now I feel like first-years don’t even know what Stack Overflow is. They just use AI. It’s the same, just faster and easier.” As students adjusted to this evolving environment, some were influenced not only by the GenAI’s potential, but also by observing their peers. Three students said they used GenAI because other students were using it. They noticed peers spending less time on work and wanted to do the same. Finally, one student mentioned using GenAI to improve their skills with the tool itself. They described experimenting with prompts and learning how to use GenAI more effectively, noting that

prompt engineering is becoming a valuable skill for the future.

In contrast, the students expressed several motivations to not use GenAI tools, which were grouped into themes: concerns about limitations, learning strategies, a commitment to academic integrity, and the lack of a need for GenAI. Table 4.5 presents the codes grouped under these themes, together with the number of students who mentioned each motivation.

Subtheme and codes	Frequency
Concerns about limitations	9
Getting false results/hallucinations	7
Risk of falling into a “rabbit hole” of unproductive use	5
Preserving learning autonomy	8
I want to be able to do the work without being dependent on GenAI	6
Improving learning through struggle	4
I want to stay actively engaged with the material	2
I am committed to academic integrity	6
I do not need GenAI for the task	5

Table 4.5: Thematic codes for student motivations not to use GenAI tools (N = 12, interviews)

One of the most frequently cited reasons for not using GenAI tools was concern about their practical limitations. Nine students expressed hesitation due to the shortcomings of the tools, with seven specifically mentioning issues such as hallucinations or false results that made them avoid GenAI for certain tasks. In some cases, students found the tools unreliable for complex assignments or lacking in explanatory depth. In addition, five students described falling into what they called a “rabbit hole” of unproductive use. When this occurred, the tool either misinterpreted the prompts or required excessive fine-tuning to produce usable output. Student I explained, “It’s terrible at figuring out why something isn’t working. I was using Linux but had to switch to Windows. I tried everything with ChatGPT, spent two hours Googling and prompting, and in the end, I just used another device and it worked in fifteen minutes. Once you start sparring with ChatGPT about the cause of a problem, you’re already too deep in it.”

Eight students cited the preservation of learning autonomy as reasons to avoid using GenAI. Six of them expressed a desire to complete academic tasks independently, aiming to maintain their skills and avoid becoming dependent on the tool. As student H phrased it, “I think once you start using it, at some point you can’t stop. And because there was already a gap, and now an even bigger one, it becomes almost impossible not to use it anymore for me.” Two students reported deliberately slowing down their workflow to stay engaged with the material, for example, by handwriting summaries or notes. Four students embraced the difficulty of academic work as a way to deepen their understanding. They described how they saw value in struggling through complex tasks. Student K stated, “I’ve always trusted that if I put in enough time and effort, I’ll find a solution. Sometimes it takes way too long and I think, this wasn’t worth it. But other times it is, because I put in the effort and got something out of it. I think people who use GenAI a lot don’t go through that process of not understanding something, putting in the work, and then finally getting it.”

Other reasons students chose not to use GenAI tools can be summarised as a commitment to academic integrity. Six students expressed wanting their work to reflect their own thinking and voiced concerns about plagiarism or the risk of being accused of misconduct. In addition, five students indicated that they simply did not need GenAI for certain tasks. These students felt confident in their ability to complete the work independently or found traditional methods more efficient. As Student D explained, “I don’t mind writing myself. I get that it’s easier with AI, but I don’t know how easily the university can detect it, and I don’t want to take that risk if I can just do it myself.”

Survey data. To assess how widespread these considerations are among the Computer Science student population, survey data was used to quantify the prevalence of reasons for using GenAI tools. The respondents were presented with a list of statements adapted from the 2025 HEPI Student Generative AI Survey [9], which closely aligned with the preliminary themes identified in the interviews. Students

could select multiple reasons that applied to them. The results are presented in Table 4.6 and Table 4.7 and provide a complementary perspective to the qualitative findings from the interviews.

The survey results indicate that the most common reason students are more likely to use GenAI tools is to save time, selected by 70 respondents. This was followed by the desire for personalised and instant support, both were selected by 55 students. Nearly half (44 responses) reported using GenAI to improve the quality of their work, while around one-third (30 responses) valued access to support outside traditional study hours or believed they learned more with GenAI. Less frequently selected reasons included improving GenAI skills (10 responses), peer influence (3 responses), and institutional encouragement (2 responses). Finally, 9 students selected having no interest at all in using GenAI tools.

Statement	Frequency
To save me time	70
To get personalised support	55
To get instant support	55
To improve the quality of my work	44
To get support outside of traditional study hours	30
I learn more if I use GenAI than if I don't	30
To improve my GenAI skills	10
Nothing: I have no interest in using GenAI tools	9
Because other students use GenAI	3
The university encourages me to use GenAI	2

Table 4.6: Reasons students are more likely to use GenAI tools (N = 91, survey)

In contrast, the survey data on why students are less likely to use GenAI tools not only quantifies the considerations found in the interviews, but also reveals new ones that were not mentioned previously. Most survey participants share the leading concern for false results or hallucinations (72 responses). This was followed by fear of being accused of cheating by the university (54 responses) and concerns about biased output (41 responses). Notably, 37 students selected that they will learn more if they do not use the GenAI tools. During interviews, this sentiment appeared more in relation to its perceived impact on their learning experience than as motivation to avoid GenAI. Concerns not mentioned in the interviews were the environmental impact (33 responses), discouragement from the university (25 responses), use of data to train GenAI models without the authors' consent (24 responses), and privacy concerns (24 responses). Barriers such as cost (13 responses) and fairness to other students (3 responses) also did not come up in the interviews. Lastly, 6 students indicated that they were fully comfortable using GenAI and saw no reason to avoid them.

Statement	Frequency
Getting false results/hallucinations	72
Being accused of cheating by the university	54
Getting biased results	41
I will learn more if I do not use GenAI	37
The environmental impact	33
The university discourages or bans the use of GenAI	25
The use of data to train GenAI models without the authors' consent	24
Not enough is done to protect my privacy	24
Tools are too expensive	13
Nothing: I am fully comfortable using GenAI tools	6
It is not fair to other students who do not use GenAI	3

Table 4.7: Reasons students are less likely to use GenAI tools (N = 91, survey)

4.2 GenAI use within academic workflows

This section presents how students integrate GenAI tools into their academic workflows. We combine data from interviews, the survey, and observed ChatGPT prompt logs. The interviews provided detailed, step-by-step accounts of how students approach academic tasks and where GenAI fits into those processes. These accounts were the basis for the individual workflow diagrams, which are included in Appendix C. Based on these individual workflows, we created a consolidated workflow diagram for each type of task and mapped GenAI use to specific steps. Based on patterns emerging from these interviews, a merged assignment workflow was developed for the survey to assess how representative these steps were for a broader student population. The survey respondents indicated how often they performed each task and how often they used GenAI tools at each step. This allowed for a ranking of GenAI adoption across workflow stages. A similar approach was taken for the exam preparation workflow. Although this workflow was not merged, it was slightly shortened for survey feasibility. To further ground these findings in real-world behaviour, prompt logs from two student project groups were analysed and mapped to the written assignment workflow. These logs provided a deeper understanding of the practical use of GenAI by students, going beyond the previous self-reports. Together, these data sources provide a rich understanding of the use of GenAI. The section begins with assignment workflows (written and programming), followed by exam preparation.

4.2.1 Assignments

This subsection presents how students use GenAI tools when working on written and programming assignments. The findings are based on semi-structured interviews and survey responses. Although the interviews distinguished between written and programming workflows, the survey combined them to reduce respondent fatigue. The following analysis first examines qualitative insights of each workflow individually, then provides quantitative insights of their combination.

Interview data. The consolidated workflow for written assignments is illustrated in Figure 4.1. Table 4.8 provides an overview of the reported use of GenAI tools throughout this process. The task’s frequency indicates how many students include it in their workflow, while GenAI use frequency reports how many utilise GenAI tools at this step.

The workflow for written assignments begins with reading the assignment brief, all students perform this step. Three students use GenAI tools at this stage to clarify vague instructions. This use was described as exploratory and typically precedes outlining. After interpreting the assignment, six students define the scope of their topic. Three of those students used GenAI to refine ideas or structure their thoughts. In these cases, the tool helps students weigh different viewpoints or formulate a research question. The next step involves consulting sources, ten students mentioned this step. Most of the students rely on traditional search methods, but seven also used GenAI tools at this step. The students explained using a tool to identify relevant materials, formulate search queries for Google and Google Scholar, or clarify unfamiliar concepts. Student G explained, “It does the searching for me. I just need to give it a good prompt, and I trust that it scans as many sources as possible. It can find ten academic sources on a topic in fifteen minutes, which would take me much longer on Google Scholar.”

Once sufficient information is collected, nine students create an outline. Most do this independently, though two use GenAI to organise their ideas. They did so by inputting key points and asking a tool to suggest a general structure or headings for sections. The drafting process varies. Some students write sequentially from beginning to end, while others begin with the main content and later add the introduction and conclusion. A third group prefers

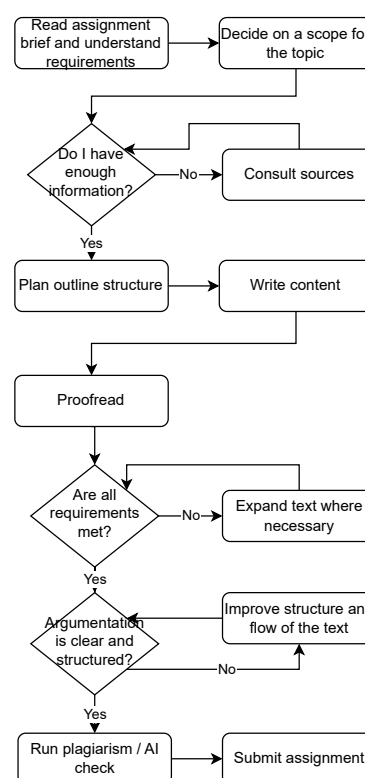


Figure 4.1: Consolidated workflow for written assignments (interviews)

Task	Frequency of task	Frequency of GenAI use
1. Read assignment brief and understand requirements	12	3
2. Decide on a scope for the topic	6	3
3. Consult sources	10	7
4. Plan outline structure	9	2
5. Write main body	12	2
6. Proofread	12	10
7. Expand text where necessary	5	3
8. Improve structure and flow of the text	9	5
9. Run plagiarism/AI check	4	1

Table 4.8: Frequency of GenAI use across tasks in the written assignment workflow (N = 12, interviews)

to write short sections and expand them incrementally. Despite these differences, most students prefer to write the content themselves. Two out of twelve students occasionally used a GenAI tool to support this process. They explained using a tool in cases of writer’s block or when drafting less central sections, such as reports accompanying programming assignments or introductions and conclusions.

Proofreading was the most common point of GenAI integration. All students performed this step, of which ten employed a GenAI tool. Students use it to identify spelling and grammar issues, assess alignment with rubrics, or highlight unclear sections. This use was often described as similar to having a second reader critique their work. All students interviewed were Dutch, and they found GenAI particularly helpful for tone and phrasing in English assignments. Five students also mentioned expanding their text where necessary at this stage; three of them used GenAI tools to assist them doing so. These students describe using a tool to meet word count requirements or elaborate on arguments. Nine students improve their writing structure and flow, five utilising GenAI tools. They enhance their writing by rewriting sentences, clarifying ambiguous phrasing, or adjusting the tone to be more academic. Finally, four students perform a plagiarism or GenAI detection check on their work before submission, one student used GenAI tools to do this.

Following the written assignments, we asked about the students’ workflow during programming assignments in the interviews. The workflow for programming assignments follows a similar structure and is depicted in Figure 4.2. An overview of the usage of the GenAI tools reported in this workflow is presented in Table 4.9.

Task	Frequency of task	Frequency of GenAI use
1. Read assignment brief and understand requirements	12	1
2. Examine provided files and/or skeleton code	10	5
3. Plan solution using pseudocode	11	5
4. Consult sources for examples or similar problems	8	5
5. Implement code	12	6
6. Add comments	6	1
7. Troubleshoot and debug	12	11
8. Test code functionality	12	1
9. Add edge cases	4	1
10. Plot visualisations	4	1
11. Clean up code	3	0

Table 4.9: Frequency of GenAI use across tasks in the programming assignment workflow (N = 12, interviews)

Students begin by reading the brief to understand the requirements. This step is similar to written assignments and assisted by GenAI tools for one student. Next, ten students examine provided files and skeleton code. Five students used GenAI to interpret unfamiliar packages or frameworks, especially when documentation is extensive or unclear. Some students also mentioned using GenAI tools to quickly identify where changes need to be made in the provided codebase or to understand how new packages relate to their existing knowledge. After reviewing the materials, students prepare their development

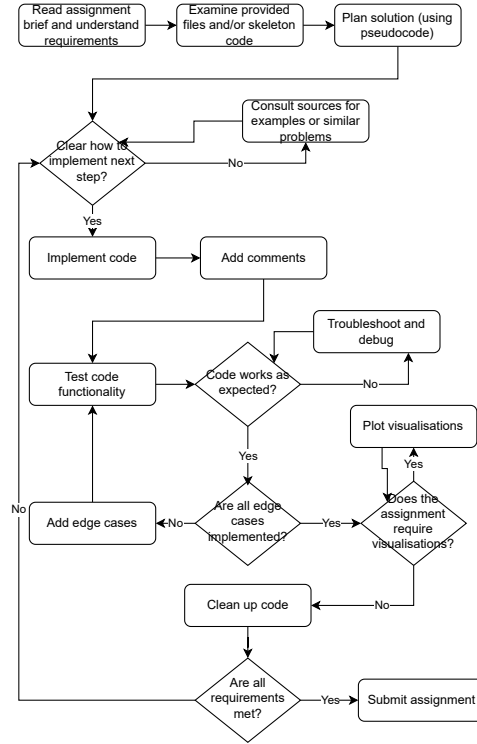


Figure 4.2: Consolidated workflow for programming assignments (interviews)

environment and begin planning their implementation. Eleven students reported planning their solution. Some do this by writing pseudocode, while others prefer a more intuitive approach and work through the steps mentally. Five students use GenAI to help structure their approach to avoid feeling overwhelmed.

As students progressed, eight students reported that they often consult sources for examples or similar problems. Stack Overflow remains a widely used resource, along with documentation and other forums. Five students mentioned that GenAI tools are an addition to this toolkit when they are uncertain about their next steps. They report using GenAI to further break down the task or to request hints that reveal part of the solution without giving it away entirely.

During implementation, GenAI assists with smaller tasks or repetitive elements for six students. Some utilise GitHub Copilot for code autocompletion. Most students handle the main logic themselves, but GenAI helps refine the smaller components. Six students described writing comments during implementation, and one student used GenAI to do this. The task for which students most frequently employ GenAI is troubleshooting and debugging, used by eleven students. Students use GenAI to identify the source of errors, understand unexpected behaviour, or fix broken code. Student F shared, “We spent six or seven hours trying to find a bug that corrupted the fake filesystem. I pasted the code into ChatGPT and it immediately found the problem, a wrong comparison operator in a loop.” Conversely, only a single student used GenAI tools to test the code, despite all completing the task. One student described using GenAI to identify edge cases. For visualisations, another student leveraged a GenAI tool for plotting code. Students tidy up their code before submission, without GenAI.

Survey data. The survey included a merged version of the written and programming assignment workflows. Respondents were asked to indicate how often they performed each task in an assignment workflow and how often they used GenAI tools during that task. 97 students finished answering questions for all tasks in the merged assignment workflow.

To assess whether the workflow structure reflects actual student behaviour of the broader sample, we first examined how frequently students perform each task. Figure 4.3a presents the distribution of responses for the assignment workflow. The percentage of students who selected “never” is relatively low across most tasks. “Revise or resolve issues” had the lowest rate of exclusion, with only 6% of students indicating they never perform this step. In contrast, “check my work for correctness and originality” had the highest omission rate, with 19% of students reporting they never do this. This suggests that the workflow is

broadly representative of how students in this population approach assignments.

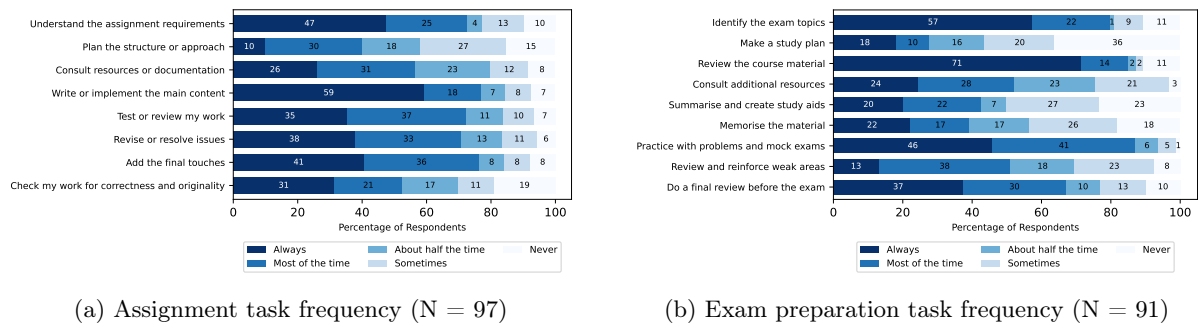


Figure 4.3: Frequency of task performance in academic workflows (survey)

To assess the extent to which students integrate GenAI tools into their assignment workflows, participants were asked to indicate how frequently they used such tools for each task. The responses were collected on a five-point Likert scale that varies from “never” to “always.” Figure 4.4 presents the full Likert distribution of responses for each task, ordered by their average adoption rank. This ranking was calculated using a method adapted from [29, 21]. The ranks were calculated by averaging the ranks of three cumulative adoption thresholds: high (students who answered “always”), medium (those who answered “always” or “most of the time”), and low (those who answered “always”, “most of the time”, or “about half of the time”). Ranks are presented together with the task labels on the left side of the figures, where lower rank values indicate higher overall adoption. In addition, each bar is segmented by response category, and the number of valid responses per task is shown on the right. These counts vary because students who indicated they never performed a task were not asked about their use of GenAI for that step.

Figure 4.4 shows the task with the highest overall adoption was “revise or resolve issues”, which received the average rank 1.0. Over 41.9% of students reported using GenAI “most of the time” or more frequently for this task, and 56.9% reported at least moderate adoption. The next most adopted tasks was “test or review my work”, with an average rank of 2.0. Although only 12.9% of students reported “always” using GenAI for this task, over half (50.5%) reported using it at least about half the time. In contrast, “understand the assignment requirements” had the lowest adoption, with an average rank of 7.5. Despite being a foundational step in the workflow, only 4.5% of students reported always using GenAI for this task, and just 26.9% reported using it at least about half the time.

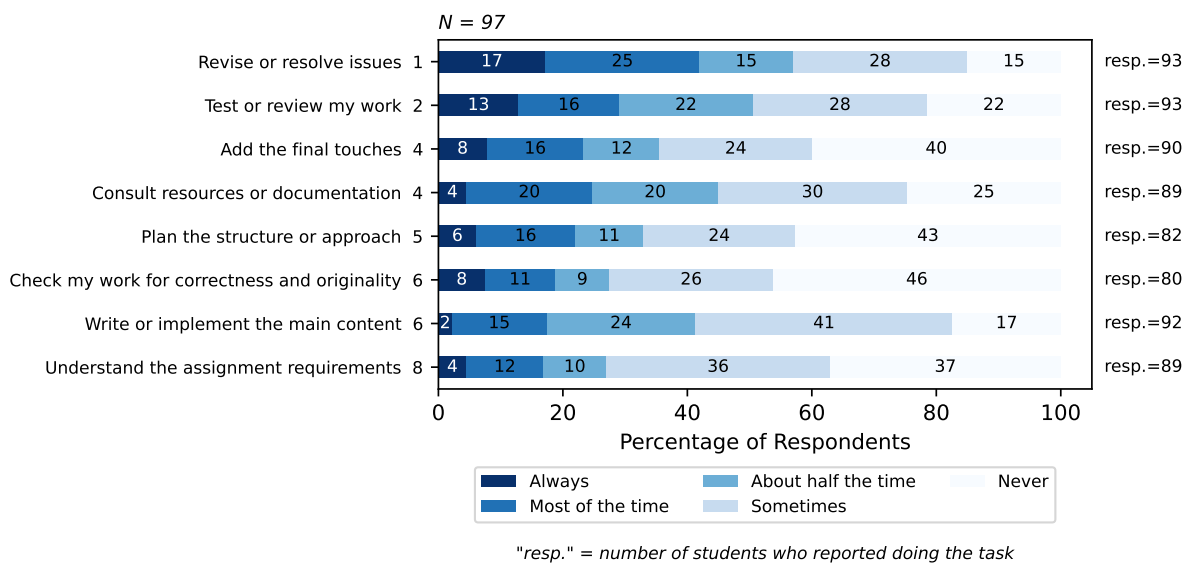


Figure 4.4: Frequency of GenAI use across assignment workflow tasks (N = 97, survey)

Some tasks with relatively high cumulative adoption percentages still received lower ranks due to uneven

performance across the three thresholds. For example, “check my work for correctness and originality” had a relatively high low-adoption percentage (41.3%) but ranked lower overall (6.33) because fewer students reported high (2.2%) or medium (17.4%) adoption. A similar pattern is observed when comparing “Consult sources or documentation” and “add the final touches”. While “consult sources” had a higher cumulative adoption at the low threshold (44.9% vs. 35.6%), it ranked slightly lower overall (4.17 vs. 4.0) because it had fewer students reporting high adoption (4.5% vs. 7.8%). These examples highlight how the ranking method, which averages independent ranks at each threshold, can produce counterintuitive results when adoption is unevenly distributed across the Likert scale. Additionally, the task “write or implement the main content” stands out visually in the figure due to the large proportion of students (41%) who reported using GenAI “sometimes”. Although this task ranked relatively low in overall adoption (6.33), it had the lowest proportion of “never” responses (17%) among all tasks.

Prompt log data. In addition to interviews and survey responses, observed GenAI use was analysed using prompt logs submitted by two student project groups. Table 4.10 presents the frequency of prompts mapped to the consolidated workflow for written assignments. This mapping offers insight into how students apply GenAI tools in different states of a real academic project.

Task	Prompt Group A	freq.	Prompt Group B	freq.
2. Decide on a scope for the topic	3		0	
3. Consult sources	41		4	
4. Plan outline structure	3		1	
5. Write main body	3		1	
6. Proofread	9		2	
7. Expand text where necessary	1		0	
8. Improve structure and flow of the text	5		2	
Generate images	67		0	

Table 4.10: Prompt frequency across written assignment workflow tasks (N = 2, prompt logs)

Table 4.10 shows that both groups used GenAI tools in multiple stages of the project, although with notable differences in intensity. Group A made extensive use of GenAI to generate images (67 prompts), a task that was not mentioned in the interviews. These images were primarily diagrams required for the assignment, along with some visuals used to enhance presentation slides. Notably, the high number of prompts does not reflect the number of images generated, but rather the number of iterations needed to refine the outputs until they met the group’s expectations. For example, a prompt from group A involved the generation of two images of the employee profile with detailed specifications, including names, roles, ages, and location. Despite these clear instructions, the group needed 15 follow-up prompts to correct layout issues, formatting errors, and visual details, such as clothing. As the iterations progressed, the prompts became increasingly detailed and showed signs of frustration. Students tried to correct layout and content issues, often using exclamations and all caps in their prompts. Nevertheless, the output repeatedly missed key specifications, resulting in a time-consuming cycle of trial and error. When asked about this in the follow-up interview, a group member acknowledged this frustration: ‘With me, you quickly notice the frustration in the prompt.’ Despite this, the experience was not seen as a reason to reduce GenAI use for this goal.

Beyond image generation, both groups used GenAI to consult sources, improve structure and flow, and proofread their writing. In interviews contextualising the logs, group members noted that GenAI was particularly helpful in discovering information that was otherwise difficult to find. For example, students used ChatGPT to estimate software licencing costs, compare implementation timelines, and generate assumptions based on limited public data. These prompts often replaced traditional search strategies, such as browsing vendor websites or consulting documentation, which students found time-consuming or incomplete. As a member of Group A explained, they turned to ChatGPT after struggling to find clear pricing information online noting that “Many of the quotes I could find online required you to request a brochure, and still gave vague answers,” whereas ChatGPT helped estimate costs per employee more efficiently. This application of GenAI contributes further to the evolution of the learning environment.

Group A described their use of ChatGPT to proofread and verify as doing a gap analysis with their own work. They reported doing an analysis themselves and then ask GenAI to do this analysis as well to see

what they could improve in their own version. Furthermore, content generation was less frequent but still present. For instance, Group B used GenAI to draft introductory descriptions of selected systems. Overall, the high number of prompts related to proofreading and refinement of text supports earlier findings that students tend to rely on GenAI more for polishing and validating their work than for initial content creation.

4.2.2 Exam preparation

In the following subsection, we discuss the use of GenAI tools by students during exam preparation. These results are based on insights from both interviews and survey data. Unlike assignment workflows, the process of preparing for exams is characterised by greater variability and less structure. This is largely because students have different personal strategies for reviewing material, ranging from summarising lecture slides to practising with problems or creating study aids.

Interview data. As illustrated in Table 4.11, students select from a variety of study methods. The consolidated workflow is shown in Figure 4.5. Exam preparation typically begins with identifying the topics covered in the exam. This involves reviewing the syllabus or other course announcements to determine what is relevant. Seven students mentioned this step, and one used a GenAI tool to get an overview of the important concepts. Four students then reported creating a study plan. Although some students mentioned using GenAI to plan in other contexts, they did not include it in their description of an exam preparation.

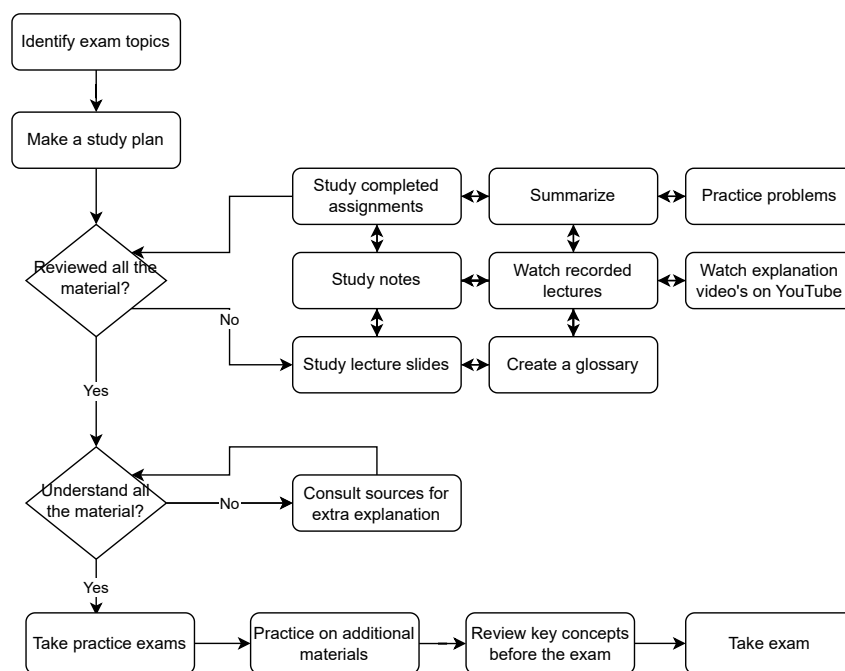


Figure 4.5: Consolidated workflow for exam preparation (interviews)

To study the material, students draw on a variety of resources. These include completed assignments (4), notes (6), lecture slides (11), and recorded lectures (1). The choice of material depends on personal preference. These materials are often used interchangeably, depending on what the student finds most helpful. Some students supplement these with external resources, such as YouTube videos (4) or other online resources (8), especially when course materials are unclear.

GenAI tools are used in several ways to support these tasks. Ten students reported summarising material and four used GenAI tools to do so. The students described pasting learning objectives into a GenAI tool and asking for a summary of the relevant theory. Three students created glossaries of key terms, one of whom used GenAI to generate the content based on slides. These tools were used to simplify and structure the material, making it easier to review.

Practice is another important component of exam preparation. Students work through exercises or past

Task	Frequency of task	Frequency of GenAI use
1. Identify exam topics	7	1
2. Make a study plan	4	0
3. Study completed assignments	4	0
4. Study notes	6	0
5. Study lecture slides	11	4
6. Summarize	10	4
7. Watch recorded lectures	1	0
8. Create a glossary	3	1
9. Practice problems	8	1
10. Watch explanation video's on YouTube	4	0
11. Consult sources for extra explanation	8	7
12. Take practice exams	10	1
13. Practice on additional material	7	5
14. Review key concepts before the exam	4	0

Table 4.11: Frequency of GenAI use across tasks in the exam preparation workflow (N = 12, interviews)

exams to test their understanding. Eight students reported practising with problems, and one used GenAI to help with this by checking their answers. Seven students state they will use extra materials for practice when they are not yet fully comfortable with the content. Five students report they use GenAI to generate new questions, mimicking course content. In contrast, only one student of ten used GenAI to support taking practice exams.

In the final stages of preparation, students review their own summaries, glossaries, or other materials. This includes last-minute revision the day or night before the exam, where the focus is on refreshing key concepts rather than learning new material. Four students reported reviewing key concepts before the exam, but none used GenAI tools during this step.

Survey data. A simplified version of this workflow as also included in the survey. Students were asked the same questions as for the merged assignment workflow. 91 students completed all questions on the workflow tasks for exam preparation.

Figure 4.3b presents the distribution of how often students reported performing each task in the exam preparation workflow. Similar to the interviews, the survey results show greater variability in task frequency compared to the assignment workflow. “Practice with problems and mock exams” and “consult additional resources” are among the most commonly performed tasks, with only 1% and 3% of students respectively indicating they never do them. In contrast, “make a study plan” and “summarise and create study aids” are less consistently performed, with 36% and 23% of student reporting they never engage in these steps. These findings suggest that while the exam preparation workflow is more flexible, the included steps still reflect common practices among the broader student population.

To evaluate how students use GenAI tools during exam preparation, participants were asked to indicate how frequently they used these tools for each task. As with the assignment workflow, the responses were collected on a five-point Likert scale and analysed using a ranking method based on cumulative adoption thresholds: high (students who answered “always”), medium (those who answered “always” or “most of the time”), and low (those who answered “always”, “most of the time”, or “about half of the time”). Tasks were then ranked independently at each threshold, and the average of these ranks was used to determine overall adoption. Lower average ranks indicate higher adoption. Figure 4.6 presents the distribution of Likert-scale responses for each task, ordered by their average adoption rank.

The task with the highest overall adoption was “summarise and create study aids”, with an average rank of 1.33. 18.3% of students reported “always” using GenAI for this task, and 39.4% reported using it at least “about half the time”. The next most adopted task was “practice with problems and mock exams”, with an average rank of 2.67. Although only 8.9% of students reported “always” using GenAI for this task, nearly 39% reported at least moderate adoption. “Consult additional resources” ranked slightly lower (3.0), primarily due to a smaller proportion of students reporting high adoption. Next, “review course material” (3.67), “do a final review before the exam” (5.17), and “review and reinforce weak areas” (6.0) show similar adoption patterns. Finally, the tasks “make a study plan” and “memorise the material”

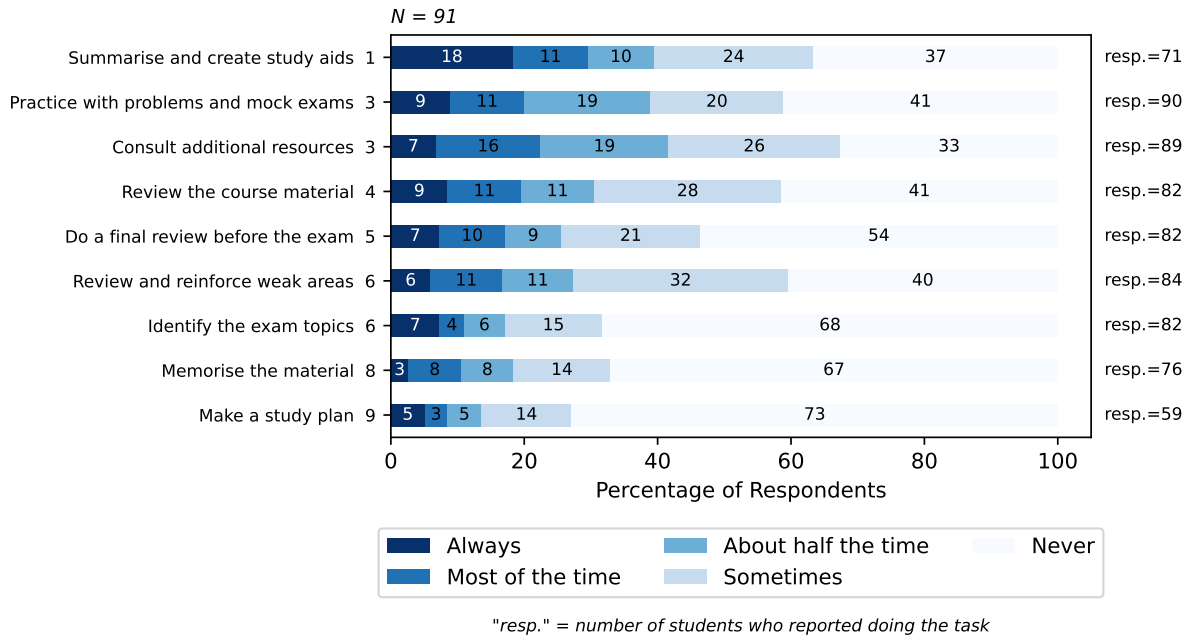


Figure 4.6: Frequency of GenAI use across exam preparation tasks ($N = 91$, survey)

received the lowest adoption ranks (8.67 and 8.0, respectively).

4.3 Student experiences using GenAI tools

While previous sections explored when and how students use GenAI tools in their academic workflows, the following focusses on how students experience these tools in practice. This section explores how students interact with GenAI, how they perceive its strengths and limitations, and how they reflect on its influence on their learning and study habits. Drawing on thematic analysis of interview data along with prompt logs, and supported by survey responses, we first explore the awareness of limitations, followed by the approaches to interacting with GenAI, which include prompt formulation and output evaluation, and subsequently, their thoughts on the broader impact of GenAI usage on learning.

4.3.1 Awareness of GenAI limitations

Before examining how students interact with GenAI tools in more detail, it is important to first consider their awareness of the tools' limitations. As discussed in subsection 4.1.2, concerns about hallucinations and biased output were among the most frequently cited reasons students were hesitant to use GenAI. These concerns not only influence whether students choose to use GenAI, but also shape how they approach and evaluate its output when they do. This section explores how students perceive these limitations in practice, including the types of issues they encounter and how frequently they arise.

Interview data. Thematic analysis revealed several ways in which students found GenAI output to be incorrect, as summarised in Table 4.12. Every student indicated experiencing a limitation of some sort. The most frequently mentioned issue was hallucinated output, reported by seven students. This included fabricated sources, irrelevant or overly broad responses, and output that disregarded instructions. Students also noted that GenAI often is not able to do complex tasks. As student B explained, "The assignments we get at university are really quite complex. It can explain the theory, because that's also available elsewhere on the internet. But I don't think it [GenAI] would be able to properly implement the code." Other limitations included contradictory responses and outdated information. Finally, one student mentioned incomplete output. They had used a GenAI tool to create an exam summary without thoroughly checking it. During the exam, they discovered the summary was incomplete.

Code	Frequency
Hallucinated output	7
Task is outside GenAI's capabilities	7
Contradictory output	3
Outdated output	2
Incomplete output	1
Total	12

Table 4.12: Thematic codes for perceived limitations of GenAI tools (N = 12, interviews)

Survey data. Although the survey did not ask students to specify which limitations they encountered, it did include a question on the perceived frequency of hallucinations. As shown in Table 4.13, over half of respondents (50.55%) reported encountering hallucinations sometimes, while an additional 20.88% experienced them about half the time. Only 4.40% said they never encountered hallucinations, 1.10% selected always, and 13.19% were unsure. These findings suggest that students are generally aware of this risk associated with GenAI output.

4.3.2 Student interactions with GenAI tools

In the next section, the student interactions with GenAI tools are presented. The students expressed several approaches to navigate the benefits and limitations of GenAI, including when they decide to use these tools during academic tasks, formulate prompts, and consequently evaluate output. Together, these reflections illustrate a growing awareness of GenAI's capabilities and limitations, and a resourcefulness among students to incorporate these tools into their work.

Hallucination frequency	Frequency	Percentage
I do not know	12	13.19%
Never	4	4.40%
Sometimes	46	50.55%
About half the time	19	20.88%
Most of the time	9	9.89%
Always	1	1.10%

Table 4.13: Perceived frequency of hallucinations in GenAI output (N = 91, survey)

Interview data. Acknowledging GenAI’s limitations, the students described various strategies to overcome these through timing, prompt engineering and output evaluation. The strategies that emerged are presented in Table 4.14. All twelve students reflected on the importance of timing in their use of GenAI tools, revealing a nuanced awareness of when and how these tools are most appropriately integrated into their academic workflows. This theme of timing captures the deliberate, reactive, and sometimes unreflective strategies of the students. All twelve students described their use of GenAI in a conditional way. They described their decisions to use or not use GenAI tools as dependent on the nature of the task, the proximity of deadlines, and the perceived learning value of completing the task independently. Many students distinguished between core activities, such as writing arguments and coding, which they felt should be done without GenAI. They believed this approach preserves the purpose of the assignment. In contrast, for more supportive or repetitive tasks, such as formatting, debugging, or referencing, GenAI could be used to enhance efficiency.

Subtheme and codes	Frequency
Timing of GenAI use	12
Conditional use	12
Reactive use	7
Intentional delay	3
Unreflective use	3
Prompt engineering	10
I provide context to the GenAI tool	10
I fine-tune output iteratively	7
I define my goal for the GenAI tool	6
I add constraints for the GenAI tool to my prompt	4
I define a role for the GenAI tool	3
I ask the tool direct questions	3
I sequence my prompts	2
I specify the format I want my output in	1
I ask the GenAI tool to motivate its output	1
I am polite in my prompts	1
Output evaluation	11
I do a surface-level review of the output	10
I check output against my knowledge and expectations	9
I verify generated sources independently	9
I edit generated content	6
I run generated code	6
I assess the reasoning in the output	2

Table 4.14: Thematic codes for student strategies in using GenAI tools (N = 12, interviews)

Seven students described a more reactive approach, turning to GenAI when they felt stuck, frustrated, or pressed for time. This use was not necessarily unreflective, but it was driven more by situational urgency than by strategic planning. These students often began with the intention to work independently but resorted to GenAI when progress stalled or as the pressure of upcoming deadlines increased. Similarly, three students reported intentionally delaying their use of GenAI until they had made a genuine attempt to complete the task on their own. These students tend to use GenAI after they have formed their own ideas, using it for validation and refinement rather than generation. Student C shared, “When it comes to using AI to solve the problem for me or to do the programming, I try to postpone that as long as possible. So only if I really get stuck or it’s just frustrating or not working”. When asked what that consideration was they were making regarding the decision to use GenAI or not, they replied: “Part of it is time. How long I’ve been working on it or stuck, and how much time I have left to finish it. Mainly also to what extent I can’t find it online, to what extent other possible solutions to the problem also don’t work.” Conversely, three students described using GenAI in a more unreflective way. They described occasions where they were driven by convenience or lack of motivation to do work by themselves. In these cases, little consideration was given to the learning value of the task, and the risk of dependency was present.

Despite these approaches, several students expressed discomfort with how frequently they relied on GenAI. This tension between convenience and integrity was described as a slippery slope. As student I explained, “One of the downsides is that it’s kind of uncomfortable to realise how much I rely on AI tools to support my studies. It’s not really something people are proud of. It’s like, should I be worried about how much I use it? You don’t really know, because no one talks about it.”

Ten students described forms of prompt engineering. A common strategy involved providing context to the tool. Ten students mentioned including assignment briefs, rubrics, or parts of their own work in their prompts to help generate more relevant and accurate responses. This was particularly useful when students wanted the tools to align with specific course requirements or build on their existing progress. Seven students also described iteratively refining their prompts until the response met their expectations. Four students reported adding constraints to their prompt to control the complexity, scope, or tone of the output. For example, they might prompt the tool to “explain it like I’m a ten-year-old” or to “only use the content I provided.” Six students defined a clear goal before prompting, such as generating practice questions or checking for logical consistency. Similarly, three students mentioned assigning the tool a role, like that of a teacher or student. Asking direct questions was another tactic employed by three students. Furthermore, two students described sequencing their prompts to break down complex tasks into smaller steps. This helped the students better understand the output and the tool not to deviate too much. One student asked the tool to justify its responses, Student G shared, “I always add ‘explain’ to the prompt. I want to know why something is wrong. That way, I can check whether the assumption is correct or not.” Other strategies mentioned by one student are specifying the format of the output and being intentionally polite in prompts, using phrases like “please” and “thank you”.

In addition to prompt engineering, eleven students also engaged in various forms of output evaluation. Ten of those students began with a surface-level review to check whether the output looked plausible. Nine students compared the output against their own knowledge or expectations. Nine students independently verified any sources provided by the tool, often using Google to confirm whether the sources were real and relevant. Student C described their process: “First I compare the information with other sources. If the tool gives a source, I check it. If it doesn’t, I ask for one and then check whether it matches. Especially when it makes factual claims, I always verify them.” Six students also reported editing the output to match their own writing style or better integrate it into their work. In a programming context, six students mentioned running the generated code to test its functionality. Two students evaluated the reasoning behind the output, assessing whether the logic was coherent and appropriate for the task by retracing GenAI’s reasoning.

Prompt log data. To better understand how students interact with GenAI tools in practice, we analysed the prompt logs from Group A and B for elements of prompt engineering, as described in the interviews. Table 4.15 presents the frequency of prompts that contain specific strategies. Some prompts contained elements of multiple approaches and were coded double.

The groups frequently included context in their prompts, such as the assignment brief, background information on the business case, or their drafts. Group A also engaged in extensive iterative refinement, particularly when generating images. Many prompts were used to adjust layout, content, or formatting. In addition, the group asked clarifying questions or requested the tool to motivate where its answers

Prompt engineering strategy	Frequency Group A	Frequency Group B
I fine-tune output iteratively	70	0
I provide context to the GenAI tool	24	6
I ask the tool direct questions	23	2
I define my goal for the GenAI tool	15	4
I specify the format I want my output in	11	0
I add constraints for the GenAI tool to my prompt	5	0
I ask the GenAI tool to motivate its output	5	0
I sequence my prompts	4	0

Table 4.15: Frequency of GenAI prompts with a prompt engineering element (N = 2, observed)

came from. The prompts often had clearly defined objectives in which the students defined what they wanted out of the interaction. Some prompts included constraints to guide the tool’s behaviour. Group A, for instance, specified that the tool should not automatically complete a task but instead assist in brainstorming or offer suggestions for improvement. Furthermore, the prompts also frequently took the form of direct questions. In two cases, Group A sequenced their prompts to structure a comparison. Group A also specified output formats, particularly for images, and described the desired features in detail. In some cases, they asked the tool to motivate its output by providing sources or justifying its reasoning. Finally, interviews with group members revealed that students did not accept GenAI output without review. Group A, for example, described comparing the tool’s suggestions with their own knowledge and expectations. A member of Group A explained, “Well, in my case I could compare it with information I had already read on the web and just brochures. And sources I had already read. So I already had a vague idea of how it should roughly be. Often it’s the case that you start such a chat with already a kind of vague idea of correct information that you have found. So you know which direction it should go. And if it is not in line with that, then I have, then I start to have doubts. Then I look at it like, okay, did I get it wrong or did you actually get it wrong?”

Survey data. While the survey did not include the full range of prompting and evaluation strategies described in the interviews, it did include a question about students’ perceived engagement with GenAI output in general. As shown in Table 4.16, the majority of respondents reported engaging with the output in an active and critical manner. Specifically, 42.86% of students reported using the output as inspiration but writing/coding everything themselves, and 37.36% selected adapting the output significantly to fit their needs. Only a small minority reported copying the output with little or no changes (2.20%), and 7.69% used GenAI only to check or review their own work.

Engagement level	Frequency	Percentage
I use the output as inspiration but write/code everything myself	39	42.86%
I adapt the output significantly to fit my needs	34	37.36%
I do not use GenAI tools	9	9.89%
I only use GenAI to check or review my own work	7	7.69%
I copy the output with little or no changes	2	2.20%

Table 4.16: Self-reported student engagement with GenAI output (N = 91, survey)

4.3.3 Student reflections on the impact of GenAI use

After exploring how students interact with GenAI tools, this final part turns to their reflections on the broader consequences of using these tools. The students shared how GenAI has influenced their learning outcomes and habits. These reflections offer insight into how GenAI is not only shaping academic tasks, but also affects students’ perceptions of effort, skill development, and the learning process itself.

Interview data. Drawing from interview data, this section presents students’ perceptions of both positive and negative impacts. Admittedly, most of the consequences discussed here are negative. However, positive experiences such as the benefits regarding productivity and support frequently served as

incentives to continue using GenAI, and thus were coded as motivations for using the tools rather than impacts.

Code	Frequency
I learn less when I use GenAI	8
I learn more if I use GenAI than if I don't	5
Disappearing skills	4
I have become lazier	4
Course content has changed	2
Total	10

Table 4.17: Thematic codes for perceived consequences of GenAI use (N = 12, interviews)

Eight students reported that using GenAI tools sometimes led to reduced learning outcomes. They described remembering less of the material or producing work with a lower quality when relying on GenAI. Four students discussed an erosion of academic skills, two from personal experience and two in reference to other students. Student G remarked: “I can’t even imagine how I would have done it without [GenAI]. I think, how on earth would I start writing? How would I plan it out?” In contrast, five students described they learned more when using GenAI. They attributed this to factors such as improved understanding of complex concepts, exposure to new vocabulary through suggested synonyms and antonyms, and the time saved on routine tasks, which allowed them to focus more deeply on higher-level thinking.

Four students described becoming lazier or procrastinating more due to the ease GenAI tools offer them. Student G explained that the knowledge that ChatGPT can quickly assist with various parts of an assignment led them to start their work later, because they relied on GenAI to help them catch up under time pressure. However, this reliance often backfired, making the final stages of the task more stressful and difficult. Similarly, a student noted that they became more impatient. They now expect answers quicker and become more frustrated when a GenAI tool cannot help them sufficiently. Finally, two students stated that course content had changed in response to GenAI. They note that some assignments now appear to be deliberately designed either to discourage the use of GenAI or with the assumption that students will use these tools as part of their workflow.

Prompt log data. Additionally, members from Group A described a shift in their expectations and behaviour since using GenAI tools. They noted becoming more impatient and less tolerant of delays, explaining that the immediate and tailored responses provided by GenAI had raised their baseline for what they consider acceptable. Compared to traditional search methods such as Google, where finding a useful answer among several sources was sufficient, they now expect instant, curated responses.

4.4 Student disclosure practices around GenAI use

While previous sections explored how and why students use GenAI tools, this section examines whether and how they disclose that use in academic contexts. Disclosure is a key aspect of responsible GenAI use, particularly in light of ongoing debates around academic integrity. However, as the findings in this section show, disclosure practices among students are inconsistent and rare. Presenting both interview insights and survey findings, this section explores the conditions making student more or less likely to disclose their use of GenAI tools. It also highlights the role of university guidance in shaping these practices. By examining students’ disclosure practices, this section provides insight into how students navigate the boundaries of GenAI use.

Survey data. The survey results on how often students disclose use of GenAI tools in their assignments show best how infrequent such disclosures are. The students were asked how often they disclose the use of GenAI tools in their academic assignments. The complete results of the survey are presented in Table 4.18. A convincing majority (82.22%) never or sometimes discloses their use of GenAI tools for assessments. In contrast, the percentages of students that disclose more often are much smaller. Only 5.56% of respondents disclose “about half the time”, 6.67% “most of the time”, and 5.56% “always.”

Disclosure frequency	Frequency	Percentage
Never	45	50.00%
Sometimes	29	32.22%
About half the time	5	5.56%
Most of the time	6	6.67%
Always	5	5.56%

Table 4.18: Self-reported frequency of GenAI use disclosure in assignments (N = 90, survey)

Interview data. Four students from the interviews reported having disclosed their use of a GenAI tool in an assignment. They did so by referencing the GenAI tool either as a source, in a paragraph, or in a comment above the function. One student also mentioned providing chat history when disclosing their use. Since in practice many students do not disclose their use of GenAI tools, discussions in the interviews often shifted toward what made students more or less likely to do so. Students mentioned that they would disclose when a course required it, although they noted that such requests are currently rare. They also cited that they would disclose when they heavily relied on a tool or when they wanted to avoid issues with plagiarism. The codes and their frequencies are presented in Table 4.19.

Code	Frequency
I am explicitly asked to disclose it or told I am allowed to use GenAI tools	5
I relied heavily on the GenAI tool to complete the task	2
I want to avoid potential issues with plagiarism or misconduct	1
Total	6

Table 4.19: Thematic codes for reasons students disclose GenAI use (N = 12, interviews)

The most common reason students gave for disclosing was being explicitly asked to or being told that the use of the tool was permitted, five students mentioned this. Students explained that they typically do not disclose GenAI use unless prompted by course guidelines. Student F noted, “I never really mention it, but I also wouldn’t lie and say I didn’t use it. Unless the course explicitly says you’re not allowed to use it. But none of our courses say you have to disclose it, so I just don’t.”

Two students said they would disclose GenAI use when they relied heavily on the tool to complete a task. This included cases where they made minimal changes to the output or used GenAI to generate substantial parts of their work. One student described using GenAI to autocomplete code, while another mentioned including a paragraph written by GenAI to demonstrate the tool’s capabilities. In these cases, students felt that the extent of their reliance warranted transparency. Finally, a student mentioned that they would disclose GenAI use as a way to avoid potential issues related to plagiarism or academic misconduct. Student G emphasised the importance of not misrepresenting AI-generated content as their own work, expressing a clear concern about upholding academic integrity and ensuring that their contributions were accurately and ethically presented.

In contrast, the students gave several reasons for not disclosing their use of GenAI in the interviews. They often felt that disclosure was unnecessary, comparing it to other online resources or tasks they could complete alone. Additionally, fears of penalties and vague institutional guidelines caused varied disclosure practices. Table 4.20 presents all codes and frequencies related to this theme.

Seven students said they did not think it was necessary to disclose because they felt that they could have come up with the same output themselves or that their use of the tools was not central to their work. They viewed GenAI as a way to accelerate their process or support their understanding, but not as a contributor to the final product. This reasoning was also applied to cases where students had significantly adapted generated output themselves and felt that the final work was their own. Additionally, three students shared the belief that an application of GenAI was similar to using other (online) resources. They felt that certain applications of GenAI, such as using it to collect sources, do not require disclosure, similar to how they would not mention using Google to discover sources. However, the students did make sure to refer to the sources they used in their work. This perspective also extended to programming tasks, where students viewed using GenAI to write small functions as comparable to copying snippets

Code	Frequency
I could have come up with the same output myself	7
I am afraid of being penalised	5
I think it is similar to using other online resources	3
There are no clear guidelines on how to disclose from the university	1
Total	8

Table 4.20: Thematic codes for reasons students do not disclose GenAI use (N = 12, interviews)

from online forums. In these cases, students did not see the tool as fundamentally different from other aids.

Furthermore, five students said they were reluctant to disclose because they fear being penalised. The students were unsure about what was allowed or acknowledged that their use might not be permitted, and therefore they avoided disclosure. Student L admitted “I don’t think it’s okay to use ChatGPT to generate code, but I do it anyway, and that’s why I don’t disclose it.” Finally, one student pointed to a lack of clear guidelines from the university as a reason for not disclosing. They were unsure what counts as GenAI use, when it should be disclosed, or how to do so. This uncertainty contributed to inconsistent practices and reliance on personal judgment of constituted acceptable use rather than institutional policy.

Survey data. The survey results show more variability in the disclosure practices of students. The respondents could select multiple applicable reasons that made them more likely to disclose GenAI use in their assignments. The results, presented in Table 4.21, show that the most frequently cited reason was being explicitly asked to disclose GenAI use (52 responses), followed closely by a desire to avoid potential issues with plagiarism or misconduct (48 responses). Clear guidelines from the university (43 responses) and a general belief in academic honesty and transparency (29 responses) were also commonly selected. Fewer students indicated that they disclose their use when they rely heavily on the GenAI tool (16 responses) or use the output with minimal changes (20 responses).

Statement	Frequency
I am explicitly asked to disclose it	52
I want to avoid potential issues with plagiarism or misconduct	48
There are clear guidelines on how to disclose from the university	43
I believe in academic honesty and transparency	29
I use the output exactly or with minimal changes	20
I rely heavily on the GenAI tool to complete the task	16
Other (please specify)	8

Table 4.21: Reasons students are more likely to disclose GenAI use (N = 90, survey)

The survey statements also included an open-text “Other” option. Most of the responses reiterated the themes of heavy reliance on a tool and the absence of clear university guidelines. Notably, one student added: “Only if it is very noticeable AI, which is almost never.” This response suggests that this student is mainly motivated to disclose when the output is sure to raise suspicion. In other words, disclosure in this context seems to be influenced more by the fear of being discovered than by ethical principles. Other responses indicated that they either did not reveal the use of GenAI or do not use GenAI tools, highlighting an oversight in the survey statements, which failed to consider these scenarios.

Likewise, the survey included a multiple-select question on what factors make students less likely to disclose their use of GenAI tools. As shown in Table 4.22, the most frequently cited reason was the absence of clear university guidelines (42 responses), followed by the belief that using GenAI is similar to consulting other online resources (40 responses). Fear of being penalised (35 responses) and the belief that coding inherently involves reusing online code (34 responses) were also common. A little over a third of respondents (33 responses) felt that disclosure was unnecessary if they had adapted the output, while the belief that there is a taboo around using GenAI tools got 30 responses. The open text responses

further illustrate the ambiguity that students experience. Several students described using GenAI in ways where they did not think disclosing is necessary, such as for brainstorming or understanding theory.

Statement	Frequency
There are no clear guidelines on how to disclose from the university	42
I think it is similar to using other online resources	40
I am afraid of being penalised	35
Coding often involves reusing code from the internet anyway	34
I don't think it is necessary if I adapt the output	33
I believe there is a taboo around using GenAI tools	30
I could have come up with the same output myself	20
Other (please specify)	15

Table 4.22: Reasons students are less likely to disclose GenAI use (N = 90, survey)

Chapter 5

Discussion

This chapter discusses the findings presented in the previous chapter in relation to the existing literature. It interprets the results through the lens of the research questions and reflects on their broader implications for higher education. In addition, it outlines the limitations of the study and proposes directions for future research.

5.1 Interpretation of results

This section addresses the three research questions that guided this thesis. We discuss how students use GenAI tools across their academic workflows, the strategies they apply when engaging with these tools, and how their choices relate to academic integrity. Each subsection connects the findings of this thesis to relevant literature and highlights key insights.

Before interpreting how students use GenAI tools in academic workflows, it is important to understand who the students in this study are. The samples in this study consisted of 12 interview participants, 97 valid survey respondents, and two project groups whose use of GenAI was observed using prompt logs. The majority of participants were enrolled in the Computer Science or Data Science and Artificial Intelligence programmes at Leiden University. Most of the students in the interviews were in their third year or higher, although the survey showed a more even split. Both bachelor’s and master’s students were represented. This disciplinary and academic experience likely contributed to the high levels of GenAI familiarity observed throughout the sample. In the survey, 71% of the respondents described themselves as “somewhat familiar” or “very familiar” with GenAI tools. Similarly, many interview participants reported frequent use outside academic context and high general comfort.

In this study, that confidence was evident both in the frequency of GenAI use and in the interactions the students described, such as prompt engineering, iterative refinement, and critical evaluation of the output. However, this also introduces a potential bias. The findings may reflect the practices of students who are more digitally literate, more motivated to explore new tools, or more comfortable navigating the risks and uncertainties of GenAI use. The background of these students could result in more successful interactions with GenAI tools. This assumption is supported by Szenftner et al. [31] and Tsekouras et al. [33] who reported on learning curve associated with GenAI use. As such, the patterns observed in this study may not generalise to students in other disciplines. Nonetheless, by focusing on this group, the study offers valuable insights into how GenAI is being integrated by students who are arguably at the forefront of this technological transformation.

5.1.1 GenAI use across academic workflows

To understand how students use GenAI tools in their academic work, we first needed to understand what that work actually looks like. This led to the development of detailed academic workflows, which served as the foundation to identify where and how GenAI tools are integrated. The workflows were constructed from interview data and subsequently validated through survey responses. The findings on these processes revealed a shift in the way students approach academic challenges. Rather than seeking to understand the underlying theory behind a problem, students increasingly turn to GenAI tools for

immediate solutions. They described asking questions such as “Why is this not working?” instead of “What is the theory behind ...?” This change reflects a broader transformation in the way students seek help. The accessibility of support that GenAI tools offer enables quick fixes, but may ultimately discourage deeper engagement with the course material.

Survey data quantified that the most common use of GenAI occurs during the “revise or resolve issues” stage of the assignment workflow, which includes tasks such as troubleshooting, debugging, and improving the structure and flow of content (Figure 4.4). This shift was most notable in the programming workflow, 11 out of 12 interviewed students reported using GenAI for troubleshooting and debugging, making it the most frequent point of integration. The students described how they would copy-paste code into a tool, often accompanied by an error message. The tool would then point out any issue that they had and suggest a solution. This application of GenAI bypasses the effort that goes into recognising the difference in error messages, understanding the theory of the concepts they are trying to implement, or basic debugging approaches. However, this shift was observed not only in the programming workflows, but also in the written assignments. Similarly, this shift was observed in written assignments. The students described using GenAI tools to improve the structure and flow of content or to extend existing work. Their use of GenAI often involved entering work into a tool and depending on the tool to “fix” the content.

This pattern is consistent with how students described the timing of their use of GenAI. Although all 12 interviewees reported using GenAI conditionally, considering the nature of the task, perceived learning value, or proximity to deadlines, seven students still reported reactive use. These students turned to GenAI when they felt stuck, frustrated, or under time pressure, often as a last resort. This reactive use suggests that GenAI is not always part of a planned learning strategy but also a tool students reach for when urgency arises. Furthermore, the motivation of the students to use GenAI tools further supports this interpretation. In interviews, seven students stated that they used GenAI to reduce the effort required to complete tasks, while five admitted that they used it to avoid work they found uninteresting or overly difficult. These motivations were echoed in the survey, where 70 students selected “to save me time” as a reason for using GenAI.

This shift in approach is not without consequence. Four students described becoming lazier or more prone to procrastination due to the ease of access that GenAI provides (Table 4.17). One student explained how the availability of GenAI led them to delay starting assignments, relying on GenAI to help them catch up under pressure. However, this made the final stages more stressful. Another student noted that they had become more impatient, expecting instant answers, and becoming frustrated when GenAI could not deliver.

At the same time, some students expressed concern about this change. Four interviewees commented on the value of struggling through complex material in the learning process. Griffin and James [11] describe this kind of effort as a productive struggle, “the process of students engaging in challenging tasks that require effort, problem solving, and perseverance, which improves their metacognition by fostering self-awareness, reflection, and strategic thinking about their learning approaches” The tension between convenience and cognitive development highlights a key challenge in integrating GenAI into learning environments. Although GenAI tools can reduce frustration and accelerate progress, they may also erode opportunities for deeper learning if used too often or too early. This does not mean that GenAI is inherently bad, but it does suggest that how and when students use these tools matters. Encouraging more intentional and reflective use may be the key to ensuring that GenAI enhances rather than erodes learning. As Fui-Hoon Nah et al. [10] caution, the ability of GenAI tools such as ChatGPT to generate high-quality answers in seconds may discourage students, particularly those with lower motivations, from investing time and effort in their assignments. This issue becomes more pressing when we consider that the GenAI detection tools are not yet accurate. Consequently, the originality and depth of student work becomes increasingly difficult to assess, raising concerns not only about academic integrity, but also about the long-term development of critical thinking and resilience [10, 11, 16].

5.1.2 Student experiences with GenAI tools

To understand student GenAI use, it is important to understand not only what they use these tools for, but how they interact with them. This includes their interactions with GenAI tools to prompt and evaluate GenAI output, but also the perceived impact this use has. Although GenAI tools offer students immediate support and increased efficiency, their growing reliance on these tools may undermine

academic self-efficacy. Even though this study’s findings reveal that GenAI tools offer students valuable support in navigating academic challenges, they also suggest that growing reliance on these tools may have unintended consequences for students’ academic self-efficacy. Self-efficacy, defined as the belief in one’s ability to succeed, plays a critical role in student motivation and learning outcomes.

The interviews revealed all but one student use GenAI at some point in their workflow. The task with the highest frequency of GenAI use, troubleshooting, similarly showed GenAI support for all these eleven students. The survey data validated these frequencies across tasks, suggesting GenAI is adopted by a large part of the student population and in numerous workflow tasks. Although many students in this study described GenAI as a helpful resource, some also reported that this reliance had begun to erode their confidence in their own abilities. Three students stated that they felt unable to keep up without GenAI, one remarked, “Once you start using it, at some point you can’t stop”. For these students, GenAI had become more than a support tool, it had become a crutch. This highlights a growing sense of dependency that may undermine students’ perceived control over their learning.

This impact on self-efficacy was also evident in the reflections of the students on skill loss. Four students described a decline in their academic abilities, either in themselves or in peers, as a result of frequent GenAI use. These experiences suggest that while GenAI may reduce short-term frustration, it can also displace the effort necessary for the cognitive processes that are essential for deeper learning. This concern is echoed in the literature. Kosmyna et al. [16] warn of the accumulation of “cognitive debt,” when students rely on GenAI without engaging critically with its output. Similarly, Tsekouras et al. [33] found that while GenAI can improve surface-level writing, it may undermine deeper reasoning and argumentation skills. Wood and Moss [34] argue that responsible GenAI use requires students to remain cognitively engaged, rather than passively accepting AI-generated content.

The risk of dependency is further complicated by the absence of structured scaffolding. The findings of this study are in contrast to Yilmaz and Karaoglan Yilmaz [35], who found that GenAI uses improved programming self-efficacy when paired with metacognitive prompts and guided reflection offered in the course. During the study, teachers asked questions such as “What questions must you ask to resolve this issue?” or “What type of inquiry can you formulate to derive a more innovative solution?” These questions encouraged students to evaluate their own thoughts and remain actively engaged. However, the difference in this case study is that students largely navigated GenAI use independently. Without instructional support, students may struggle to develop the reflective habits needed to use GenAI as a tool for learning rather than a shortcut. This aligns with the findings of Wood and Moss [34], who argue that reflection is a key part of responsible GenAI use.

Although some students in this study reported positive learning outcomes, such as improved understanding of complex concepts or exposure to new vocabulary, these benefits were often framed in terms of productivity and convenience. For example, students appreciated how GenAI could simplify dense material or generate practice questions. These experiences suggest that GenAI can support self-efficacy when used to scaffold learning, particularly at lower cognitive levels [30]. However, when GenAI becomes the default response to difficulty, it may reduce students’ willingness to engage in the productive struggle discussed previously [11]. This habit then has the potential to further diminish their belief in their own ability to succeed, leading to a vicious cycle that further erodes student development.

5.1.3 The impact of disclosure of GenAI use on academic integrity

Despite the widespread use of GenAI tools, survey data revealed that students rarely disclose their use of GenAI. The findings show that this is often due to unclear guidelines, fear of penalties, or because students do not believe it is necessary to disclose an application. This lack of transparency complicates efforts to uphold academic integrity and highlights the urgent need for institutional guidance on responsible GenAI use.

Survey data revealed that 82.22% of students disclose their use of GenAI “never” or only “sometimes,” with just 5.56% reporting that they “always” disclose it. When students do disclose, their motivations tend to be extrinsic: the most frequently cited reasons were being explicitly asked to disclose, avoiding accusations of plagiarism or misconduct, and the presence of clear institutional guidelines. In contrast, the intrinsic motivation to disclose appears relatively low. Only 29 students selected “I believe in academic honesty and transparency” as a reason to disclose, suggesting that ethical reasoning alone is not a strong driver of disclosure practices.

Students who chose not to disclose often did so because they did not believe it to be necessary. They gave several reasons why in the interviews and the survey. Some students felt that if they had significantly adapted the output or could have produced it themselves, disclosure was unnecessary. Others compared their use of GenAI to consulting sources such as Google, Stack Overflow, or even a friend. They reasoned that it is not customary to disclose where you found a source, provided that the source itself is appropriately cited. These findings suggest that students are not necessarily trying to deceive, but rather operate within a grey zone shaped by ambiguity and personal judgement of what constitutes acceptable use. However, this lack of transparency complicates efforts to uphold academic integrity. As Eke [7] and Rasul et al. [24] argue, the unacknowledged use of GenAI tools undermines the principles of fairness, responsibility, and trust that form the foundation of academic work.

The unacknowledged use of GenAI undermines these principles not only because it misrepresents the origin of ideas, but also because it conceals the potential presence of hallucinated or misleading content [3]. One of the most important risks associated with GenAI use is hallucination, the generation of plausible but factually incorrect or entirely fabricated information. The students in this study demonstrated a high level of awareness of this limitation. In interviews, the occurrence of hallucinations was the most frequently cited concern, mentioned by 7 out of 12 participants. The survey data reinforced this. 72 students selected hallucinations as a reason why they were less likely to use GenAI, and 65 selected that they encountered hallucinated output “sometimes” or “about half the time.” This awareness may be attributed to the students’ technical background, which likely equips them with a better understanding of how GenAI models are trained and where their limitations lie.

Despite this awareness, the risk to academic integrity remains significant. As Rasul et al. [24] point out, hallucinations can lead students to intentionally include fabricated or misleading content in their work. The risk is particularly pronounced when students lack the domain knowledge to detect inaccuracies or when they rely on GenAI to form their perspective. Other scholars have echoed this concern. Eke [7], Kosmyrna et al. [16], Fui-Hoon Nah et al. [10], Knoth et al. [15], and Sabzalieva and Valentini [28] all highlight the danger that students may unknowingly internalise or reproduce hallucinated or biased content. These risks are amplified when GenAI use is not disclosed, as educators are left unaware of the tool’s influence on the student’s work and cannot assess the reliability of the underlying information. This challenge underscores the importance of fostering critical evaluation skills in GenAI-supported learning. As Kosmyrna et al. [16] argue, students who lack these skills are more likely to internalise shallow, inaccurate, or biased perspectives.

The confusion around disclosure is further exacerbated by inconsistent or absent institutional guidance. Several students expressed uncertainty about what constitutes GenAI use, when it should be disclosed, and how to do so. As Bozkurt [1] commented, we are “experiencing the dilemma of whether we are chatting, cheating, or co-creating when employing generative AI in academic processes.” This aligns with the European Commission’s [3] call for “living guidelines” to support responsible GenAI use in research and education. Bozkurt [1] similarly advocates for structured frameworks such as aiTARAS, which encourage students to disclose not only direct contributions from GenAI, but also more indirect forms of assistance, such as idea generation or structural feedback.

The imbalance between extrinsic and intrinsic motivation to disclose suggests that institutional policy can play a powerful role in shaping student behaviour. When disclosure is explicitly requested or clearly allowed, students are more likely to comply. Conversely, in the absence of clear expectations, students default to personal judgement and often decide on non-disclosure. This highlights the need for the university to move beyond punitive messaging and toward constructive, transparent policies that normalise responsible GenAI use. As Sabzalieva and Valentini [28] emphasise in the UNESCO guide, fostering a culture of integrity in the GenAI era requires not only rules, but also open dialogue, ethical literacy, and shared understanding between students and educators.

5.2 Limitations

Several limitations should be acknowledged when interpreting the findings of this study. First, the research was conducted as a single case study at Leiden University, focusing exclusively on students enrolled in Computer Science-related programmes. Although this design allowed in-depth exploration of student experiences within a specific institutional and disciplinary context, it limits the generalisability of the findings to other disciplines and institutions. This is illustrated by a comparison with the HEPI 2025 Student Generative AI Survey Freeman [9]. The survey questions on student motivations for using

GenAI tools in this study were adapted from this study. Interestingly, the top four motivations in this study, saving time, personalised support, instant support, and quality improvement, can also be found in the top four of the HEPI survey. The difference, though, is that “to improve the quality of my work” was selected more often than the support statements. However, the percentages in this study are notably higher. For example, 76.92% of students in this study selected “to save me time,” compared to 51% in the HEPI survey. Similarly, 79.12% of students in this study cited hallucinations as a reason to avoid GenAI, compared to 51% in the HEPI survey. These differences may be attributed to the disciplinary focus of this study. Although the HEPI survey sampled a broad population of undergraduate students across disciplines in the UK, this study focused specifically on Computer Science students, who are likely to be more familiar with GenAI tools and more confident in their use. This was also reflected in the demographics of our study and aligns with HEPI’s own findings that students in STEM fields report higher enthusiasm for GenAI and are more likely to use it regularly [9].

Another limitation of this study is its reliance on self-reported data. Although interviews and the survey provided rich insight into students’ perceptions, motivations, and reported behaviours, these methods are inherently subject to biases such as selective recall and social desirability. Students may unintentionally misrepresent their GenAI use, either by overstating responsible practices or underreporting behaviours they perceive as academically questionable. For example, the students interviewed revealed little about their disclosure practices and the discussions often shifted to what they considered acceptable use rather than what they actually disclosed. This trend is also reflected in the survey data: only 2% of the respondents indicated that they “always” use GenAI to write or implement the main content, while significantly more selected “most of the time” (15%), “about half of the time” (24%), or “sometimes” (41%). This pattern may suggest that students were dissuaded from selecting “always” due to the general perception that such use borders on plagiarism. Although participation in the study was anonymous, this example illustrates how social desirability bias may still have influenced students’ responses.

To mitigate this bias, the study included a third data source. The prompt logs submitted by two project groups provided observational insights on how students used GenAI in practice. However, the sample size for these observational data was very limited. As a result, while the prompt logs were useful for contextualising and exemplifying patterns identified through other methods, they were not sufficient to independently lead to new patterns or support broader generalisations.

Third, the sample size was relatively small, particularly for the qualitative components. Although the interview sample was diverse in terms of academic year and GenAI familiarity, it may not fully capture the range of student experiences. Similarly, the ChatGPT prompt logs were limited to a single course and a very small number of student groups, which restricts the scope of observed behaviours. Finally, all interviews were conducted in Dutch. Dutch transcripts were analysed and the quotes translated into English for the study. Despite efforts to maintain meaning, slight nuances may have been altered in translation.

5.3 Further research

This study opens several promising directions for further investigation into the role of GenAI in higher education. First, institutional policies on GenAI use remain fragmented and inconsistent. Future research could examine how universities are developing frameworks for responsible use, disclosure, and assessment redesign in response to GenAI. Disclosure frameworks, such as aiTARAS [1] offer a promising starting point, but need to be evaluated in academic settings. Further research could explore how students interpret and apply such frameworks and whether they improve the low disclosure rate observed in this study.

In addition, as discussed previously, this study might not generalise to other disciplines and cultures. Therefore, future research should expand the sample size and include students from a broader range of disciplines, institutions, and even possibly nationalities. Comparative research across fields, such as humanities versus STEM, may reveal important differences in how GenAI is perceived, used, and evaluated. For example, students in writing-intensive disciplines may engage with GenAI differently than those in technical fields, and (institutional) culture may shape norms around disclosure and tool use.

Furthermore, the survey provided valuable quantitative validation of many patterns observed in the interviews. However, not all patterns had the opportunity to be represented in the survey. These

include students’ reflections on the timing of GenAI use, such as intentionally delaying use to preserve learning value or turning to GenAI reactively under time pressure, which were not captured in the survey. Other insights, such as some (de)motivators for GenAI use, students’ interpretations of what constitutes “acceptable” use, were not captured in the survey. Future research could build on these insights by designing more targeted surveys that include these factors, or by incorporating open-ended questions to capture emerging practices. Additionally, some findings, particularly those related to student interactions with GenAI tools, such as the placement of GenAI in workflows, prompt engineering strategies, and output evaluation, may be better validated through a larger and more diverse sample of observed prompt logs. Expanding this data set would allow researchers to compare reported versus actual use, identify patterns in prompt formulation, and assess how students interact with GenAI tools in real academic contexts.

For instance, this study revealed that students employ a range of interaction strategies to improve the reliability and relevance of GenAI output. Almost all interview participants described ways to structure their prompts to improve the quality of the output. These include providing context in prompts, refining queries iteratively, and checking the plausibility of responses. In addition, the prompt logs similarly showed these methods in action. In addition, the students described evaluating the output of GenAI tools. They explained reviewing GenAI output for plausibility, comparing it to their knowledge, verifying sources, and editing the content to match their own voice. In programming contexts, they tested generated code and assessed its logic. These practices align with recommendations from Knoth et al. [15], Lee and Palmer [18], and Wood and Moss [34], who emphasise the importance of intentional and reflective interaction with GenAI tools. However, the absence of survey quantification and the limited sample size of observed prompt logs make it difficult to generalise these findings across the broader student population. Future research should therefore expand the use of observational data, ideally across a larger and more diverse set of academic tasks. This extension could validate self-reported behaviours and uncover practices that may not be visible through interviews or surveys alone. A more systematic investigation into how students interact with GenAI would help clarify the role these interactions play in mitigating risks such as hallucinations and in fostering responsible use of GenAI in education.

Finally, while this study focused on how students independently integrate GenAI tools into their academic workflows, future research should explore the role of instructional scaffolding in shaping more reflective and intentional interactions. Platforms such as Packback and other AI-augmented learning environments offer AI-powered features specifically designed to enhance student engagement, critical thinking, and deep learning [34]. However, the effectiveness of such scaffolding in broader educational contexts remains underexplored. Future studies could evaluate how different instructional designs, ranging from embedded GenAI tutors to scaffolded prompt engineering exercises, affect student motivation, critical thinking, and academic integrity. Comparative research across tools and disciplines would help clarify which interventions best support responsible GenAI use, and under what conditions they are most effective.

Chapter 6

Conclusion

This thesis explored how Computer Science students at Leiden University integrate Generative AI (GenAI) tools into their academic workflows. This case study used a mixed-methods approach, including interviews, a survey, and prompt logs, to examine the usage of GenAI by students. Using this method, it examined when and why students use GenAI, how they experience these tools, and how their choices affect academic integrity. The findings offer a student-centred perspective on the opportunities and challenges of GenAI in higher education. The upcoming subsections will summarise the findings on the research questions, present an overview of the contributions, and propose future research directions.

6.1 Answers to the research questions

How do Computer Science students use GenAI tools at different stages of their academic workflows?

Students apply GenAI in a wide variety of academic tasks, with the highest adoption occurring in later stages such as debugging, proofreading, and revising. In programming assignments, GenAI is frequently used to troubleshoot errors and interpret unfamiliar code. In written assignments, it supports grammar correction, structural improvements, and source consultation. During exam preparation, students use GenAI to summarise material, generate practice questions, and seek additional explanations. A key finding is the shift in the way students approach academic challenges. Rather than deeply engaging with the underlying theory or problem-solving processes, students increasingly turn to GenAI for immediate answers. For example, instead of asking “What is the theory behind this?”, students often ask “Why is this not working?” This reflects a larger transformation in the way students seek support. This shift has implications for learning. Although GenAI reduces frustration and accelerates progress, it may also discourage deeper engagement and reduce opportunities for what Griffin and James [11] call “productive struggle.” Several students acknowledged this tension, expressing concern that reliance on GenAI could erode their ability to work through complex problems independently.

How do Computer Science students experience using GenAI tools?

Students’ experiences with GenAI are shaped by a mix of enthusiasm, caution, and evolving habits. Many students appreciate the productivity gains and personalised support that GenAI offers, especially when traditional resources are unavailable. They employ a variety of strategies to improve GenAI output, including prompt engineering and output evaluation. However, engagement levels vary. Some students use GenAI critically and intentionally, while others rely on it reactively or unreflectively. This reactive use can lead to dependency, reduced learning, and a decrease in academic self-efficacy. In conclusion, GenAI offers immediate support and efficiency, but reliance on these tools may undermine self-efficacy. The student experience is marked by a tension between convenience and cognitive development, highlighting the need for reflective use and instructional scaffolding.

How do student choices about disclosure of GenAI use affect academic integrity?

Disclosure practices are inconsistent and often absent. Students are more likely to disclose GenAI use when explicitly asked or when they fear being penalised. Many believe that disclosure is unnecessary if the output is adapted or used for support. This ambiguity is compounded by the lack of institutional guidance. Students rely on their personal judgment to determine what constitutes acceptable use, leading to varied practices. Although students are aware of risks such as hallucinations and biased output, the absence of clear policies makes it difficult to uphold academic integrity. This underscores the urgent need for universities to establish transparent policies, foster open dialogue, and support students in navigating the ethical dimensions of GenAI use.

In conclusion, students are actively experimenting with GenAI to support their academic work. They apply GenAI in a wide range of academic tasks, describe various prompting efforts, and develop personal strategies to make these tools work for them. However, when used without reflection or an intentional strategy, this experimentation risks compromising deeper learning and academic integrity, which highlights the urgent need for transparent policies and responsible use frameworks.

6.2 Contributions

This thesis contributes a student perspective to the growing body of literature on GenAI in education. It maps GenAI integration across academic workflows and highlights a spectrum of interaction. This understanding on a task level offers a practical lens for understanding GenAI's role in learning. The study reveals how students navigate GenAI use independently, often without institutional support, and how this autonomy shapes their learning experiences. It also documents the gap between GenAI adoption and disclosure, underscoring the need for clearer ethical frameworks and academic policies. Together, these contributions offer a foundation for informing responsible and effective GenAI practices in higher education.

6.3 Future work

Future research should expand beyond Computer Science to include students from other disciplines and institutions. Comparative studies could reveal how the use of GenAI varies between fields and institutions. Furthermore, larger-scale observational data, such as prompt logs, could validate self-reported behaviours and uncover unspoken practices. In addition, there is a need to evaluate disclosure frameworks such as aiTARAS in academic settings. Universities should develop clear and actionable guidelines for the use and disclosure of GenAI and integrate these into courses. Instructional scaffolding, such as metacognitive prompts and structured reflection, can help students engage with GenAI more intentionally and avoid overreliance. Finally, future surveys should explore emerging themes such as the timing of GenAI use, perceived skill erosion, and the evolving role of GenAI in shaping academic habits.

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Appendix A

Interview Guide A

A semi-structured interview guide. Estimated time: 1 hour

Introductie (5 min) Bedankt dat je mee wil doen aan dit interview! Mijn naam is Emma en ik studeer Informatica & Economie hier aan de Universiteit Leiden. Dit gesprek maakt deel uit van mijn onderzoek naar hoe studenten Generative AI-tools gebruiken in hun studie, en wat voor effect dat heeft op hun manier van leren. Met GenAI-tools bedoel ik tools, zoals ChatGPT of NotebookLM, die zelfstandig content kunnen maken, zoals tekst, code, audio of afbeeldingen. Dit interview is vrijwillig en duurt ongeveer een uur. Je mag op elk moment pauzeren of stoppen, dat is helemaal prima.

Alles wat je vertelt wordt vertrouwelijk behandeld en anoniem verwerkt. Dat betekent dat jouw naam en andere persoonlijke gegevens nergens zullen worden genoemd, en dat docenten of anderen binnen je opleiding dit niet te zien krijgen. Met jouw toestemming neem ik het gesprek op, zodat ik het later goed kan analyseren. De opname wordt alleen gebruikt voor mijn scriptie. Als je besluit dat je toch niet wil dat jouw gegevens worden gebruikt, kun je op elk moment een bericht sturen naar mij [checken dat ze mijn nummer nog hebben]. Dan verwijder ik alle herleidbare gegevens permanent uit mijn data.

Heb je hierover vragen voordat we beginnen? Dan ga ik nu de opname starten.

Ik begin graag even met een paar korte vragen:

- Welke studie doe je en in welk jaar zit je nu?
- Gebruik je GenAI tools, zoals ChatGPT of NotebookLM, buiten je studie, en waarvoor gebruik je die dan?
- Hoe comfortabel ben je met het gebruik van GenAI tools?

Workflows

- Gebruik je GenAI tijdens je studie en hoe gebruik je dit dan? Denk aan welke tools, hoe vaak en bij welke taken.
 - Waarom gebruik je het wel/niet? (wat is hier je overweging?)

In dit deel van het interview wil ik graag met je stilstaan bij hoe je omgaat met verschillende soorten studieopdrachten. We gaan het hebben over een schrijfoopdracht, een programmeertaak en tentamenvoorbereiding. Het gaat hierbij niet om een specifieke opdracht die je al gedaan hebt, maar meer om hoe je in het algemeen zulke opdrachten aanpakt. Probeer bij je antwoorden dus te denken aan hoe je meestal te werk gaat bij dit soort opdrachten.

Schrijfoopdracht Bijvoorbeeld het schrijven van een paper, verslag, of projectrapport.

- Kan je stap voor stap uitleggen hoe je een schrijfoopdracht aanpakt? Begin bij het moment waarop je de opdracht krijgt tot het moment waarop je hem inlevert. Ik zal deze stappen uittekenen in een procesdiagram en bij jou valideren. Benoem in je antwoord ook dingen waarvan je evt. denkt dat ze vanzelfsprekend zijn, zoals bijvoorbeeld het lezen van de vraag.

- Gebruik je op een of meerdere momenten in dit proces GenAI tools? Zo ja, waar? Ik zal deze momenten markeren in mijn schets.
 - Waarom zou je de GenAI tool daar gebruiken?
 - Hoe zorg je dat de output je gewenste kwaliteit heeft?
 - Hoe bepaal je of je output bruikbaar is? Waar let je op om te beoordelen of je het kunt gebruiken in je eigen werk?
 - Geef je dit gebruik van de GenAI tool aan in je opdracht? Zo ja, hoe geef je dit gebruik aan?
- Heb je een voorbeeld van een keer dat GenAI je goed geholpen heeft bij een schrijfoopdracht? Wat gebeurde er precies?
- Heb je een voorbeeld van een keer dat GenAI je niet goed geholpen heeft bij een schrijfoopdracht? Wat gebeurde er precies?

Programmeertaak Bijvoorbeeld het maken van een programmeeropdracht voor een vak of project.

- Kan je stap voor stap uitleggen hoe je een programmeeropdracht aanpakt? Begin bij het moment waarop je de opdracht krijgt tot het moment waarop je hem inlevert. Ik zal deze stappen uittekenen in een procesdiagram en bij jou valideren.
- Gebruik je op een of meerdere momenten in dit proces GenAI tools? Zo ja, waar? Ik zal deze momenten markeren in mijn schets.
 - Waarom zou je de GenAI tool daar gebruiken?
 - Hoe zorg je dat de output je gewenste kwaliteit heeft?
 - Hoe bepaal je of je output bruikbaar is? Waar let je op om te beoordelen of je het kunt gebruiken in je eigen werk?
 - Geef je dit gebruik van de GenAI tool aan in je opdracht? Zo ja, hoe geef je dit gebruik aan?
- Heb je een voorbeeld van een keer dat GenAI je goed geholpen heeft bij een programmeeropdracht? Wat gebeurde er precies?
- Heb je een voorbeeld van een keer dat GenAI je niet goed geholpen heeft bij een programmeeropdracht? Wat gebeurde er precies?

Tentamenvorbereiding

- Kan je stap voor stap uitleggen hoe je een tentamen voorbereid? Ik zal deze stappen uittekenen in een procesdiagram en bij jou valideren.
- Gebruik je op een of meerdere momenten in dit proces GenAI tools? Zo ja, waar? Ik zal deze momenten markeren in mijn schets.
 - Waarom zou je de GenAI tool daar gebruiken?
 - Hoe zorg je dat de output je gewenste kwaliteit heeft?
 - Hoe bepaal je of je output bruikbaar is? Waar let je op om te beoordelen of je het kunt gebruiken in je eigen werk?
- Heb je een voorbeeld van een keer dat GenAI je goed geholpen heeft tijdens je tentamenvorbereiding? Wat gebeurde er precies?
- Heb je een voorbeeld van een keer dat GenAI je niet goed geholpen heeft tijdens je tentamenvorbereiding? Wat gebeurde er precies?

Overige activiteiten Anders dan schrijven, programmeren en tentamens voorbereiden, zijn er nog andere studiegerelateerde activiteiten waarvoor je GenAI gebruikt? Zo ja, welke?

Voor deze activiteit,

- Kan je stap voor stap uitleggen hoe hoe je [dit doet]? Ik zal deze stappen uittekenen in een procesdiagram en bij jou valideren.
- Gebruik je op een of meerdere momenten in dit proces GenAI tools? Zo ja, waar? Ik zal deze momenten markeren in mijn schets.
 - Waarom zou je de GenAI tool daar gebruiken?
 - Hoe zorg je dat de output je gewenste kwaliteit heeft?
 - Hoe bepaal je of je output bruikbaar is? Waar let je op om te beoordelen of je het kunt gebruiken in je eigen werk?
 - Geef je het gebruik van de GenAI tool aan [bij de activiteit]? Zo ja, hoe geef je dit gebruik aan?
- Heb je een voorbeeld van een keer dat GenAI je goed geholpen heeft tijdens je [activiteit]? Wat gebeurde er precies?
- Heb je een voorbeeld van een keer dat GenAI je niet goed geholpen heeft tijdens je [activiteit]? Wat gebeurde er precies?

Algemeen

- Heb je het gevoel dat het gebruik van GenAI je manier van studeren heeft veranderd? Op welke wijze?
- Wat zijn de belangrijkste voor- of nadelen die je hebt ervaren bij het gebruik van GenAI voor je studie?

Afsluiting (5 min)

- Zijn er nog dingen die je wil toevoegen?
- Heel erg bedankt voor je deelname.

Appendix B

Interview Guide B

Introductie (5 min) Bedankt dat je mee wil doen aan dit interview! Mijn naam is Emma en ik studeer Informatica & Economie hier aan de Universiteit Leiden. Dit gesprek maakt deel uit van mijn onderzoek naar hoe studenten Generative AI-tools gebruiken in hun studie, en wat voor effect dat heeft op hun manier van leren. Met GenAI-tools bedoel ik tools, zoals ChatGPT of NotebookLM, die zelfstandig content kunnen maken, zoals tekst, code, audio of afbeeldingen. Dit interview is vrijwillig en duurt ongeveer een uur. Je mag op elk moment pauzeren of stoppen, dat is helemaal prima.

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Heb je hierover vragen voordat we beginnen? Dan ga ik nu de opname starten.

Ik begin graag even met een paar korte vragen:

- Welke studie doe je en in welk jaar zit je nu?
- Gebruik je GenAI tools, zoals ChatGPT of NotebookLM, buiten je studie, en waarvoor gebruik je die dan?
- Hoe comfortabel ben je met het gebruik van GenAI tools?

Workflows

- Gebruik je GenAI tijdens je studie en hoe gebruik je dit dan? Denk aan welke tools, hoe vaak en bij welke taken.
 - Waarom gebruik je het wel/niet? (wat is hier je overweging?)

In dit deel van het interview wil ik graag met je stilstaan bij hoe je omgaat met studieopdrachten. Vandaag gaan we specifiek kijken naar hoe je GenAI daadwerkelijk hebt gebruikt bij een specifieke opdracht voor het vak IBIA.

[Laat de student het bestaande workflowdiagram bekijken.]

- Herken je jezelf in deze workflow?
- Zou je iets willen toevoegen of aanpassen voor deze specifieke opdracht?
- Voor elk moment waarop GenAI is gebruikt (gebruik de verantwoording als leidraad):
 - Waarom zou je de GenAI tool daar gebruiken? Wat maakte dat je op dat moment dacht: “Nu kan GenAI mij helpen”?

- Hoe zorg je dat de output je gewenste kwaliteit heeft? Hoe ben je tot deze specifieke formulering van de prompt gekomen? Had je al een idee van wat voor soort antwoord je wilde krijgen?
- Hoe bepaal je of je output bruikbaar is? Waar let je op om te beoordelen of je het kunt gebruiken in je eigen werk?

Algemeen

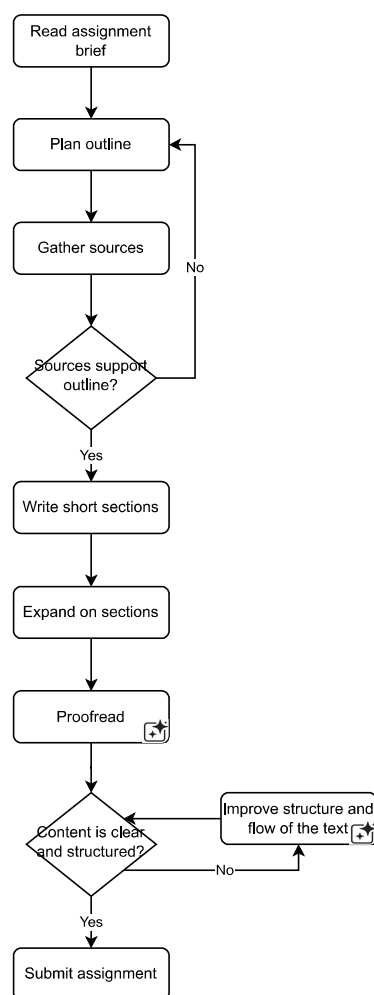
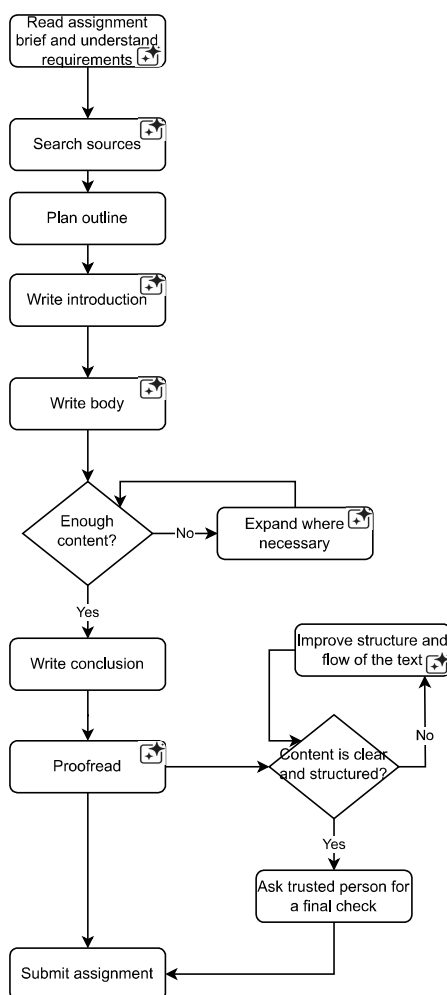
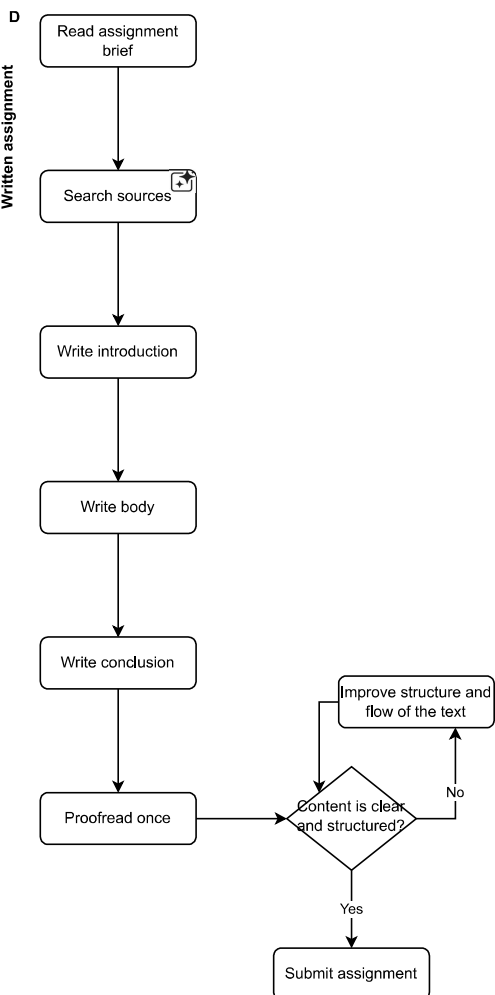
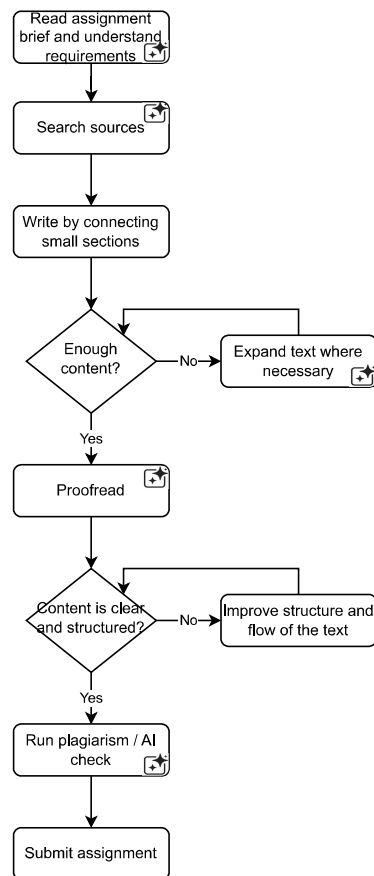
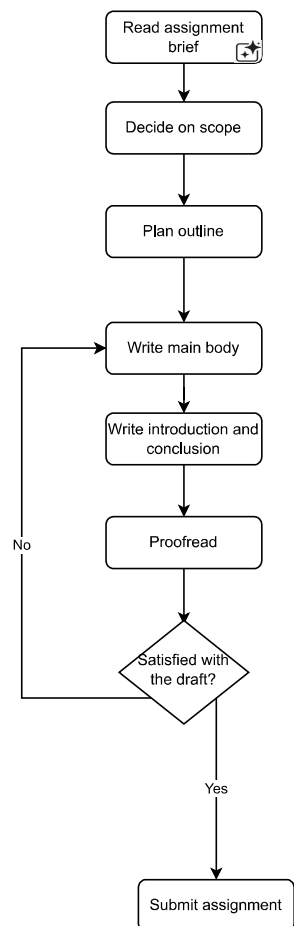
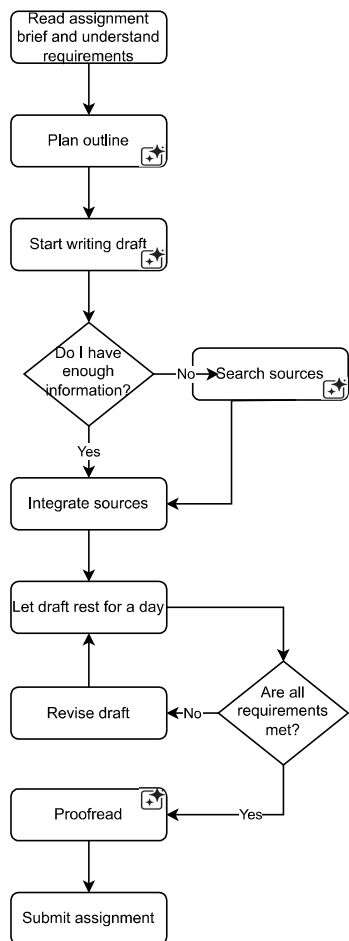
- Heb je het gevoel dat het gebruik van GenAI je manier van studeren heeft veranderd? Op welke wijze?
- Wat zijn de belangrijkste voor- of nadelen die je hebt ervaren bij het gebruik van GenAI voor je studie?

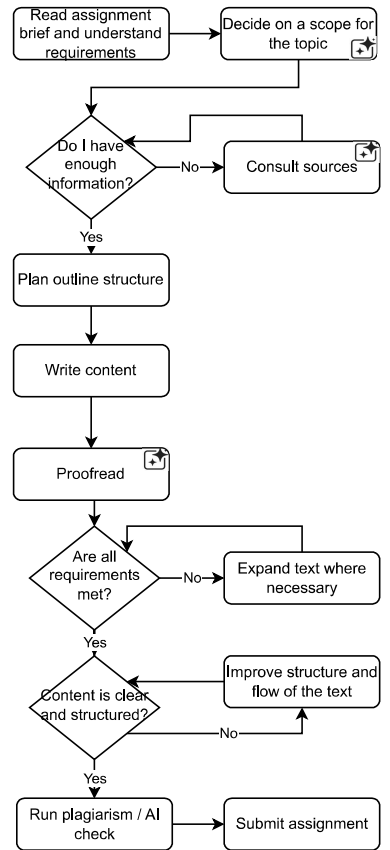
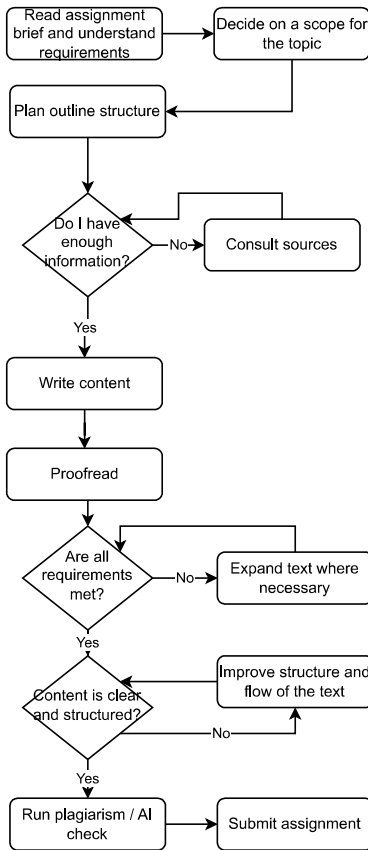
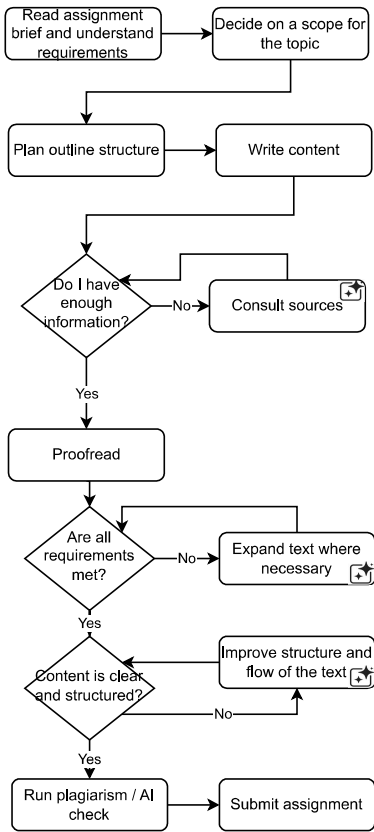
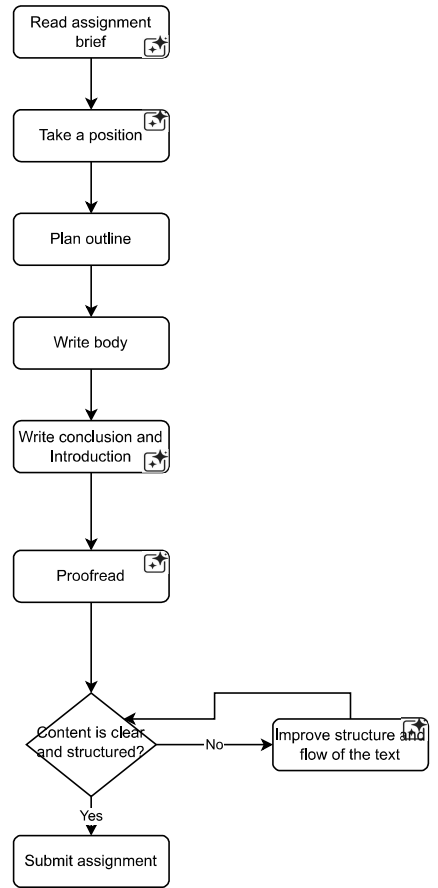
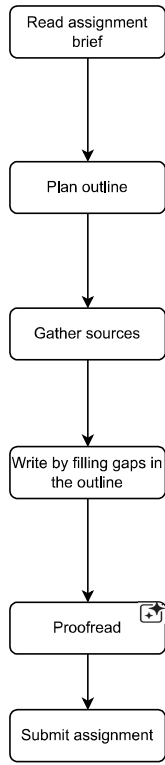
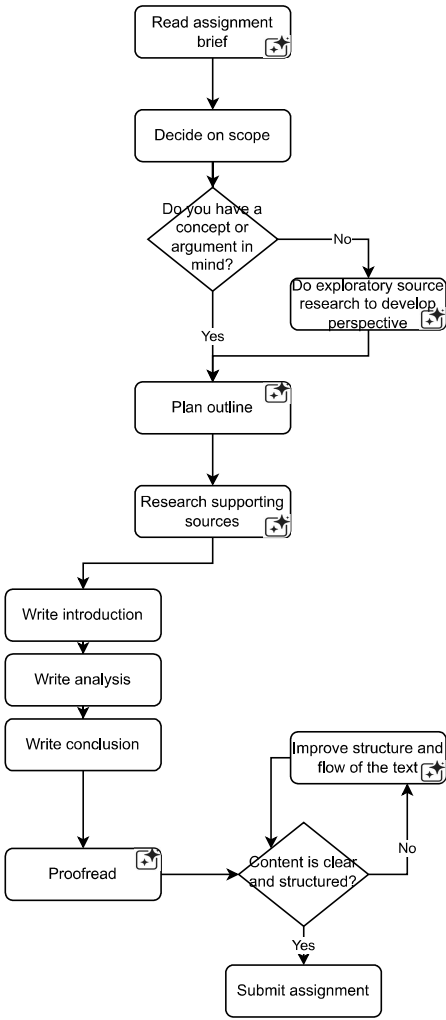
Afsluiting (5 min)

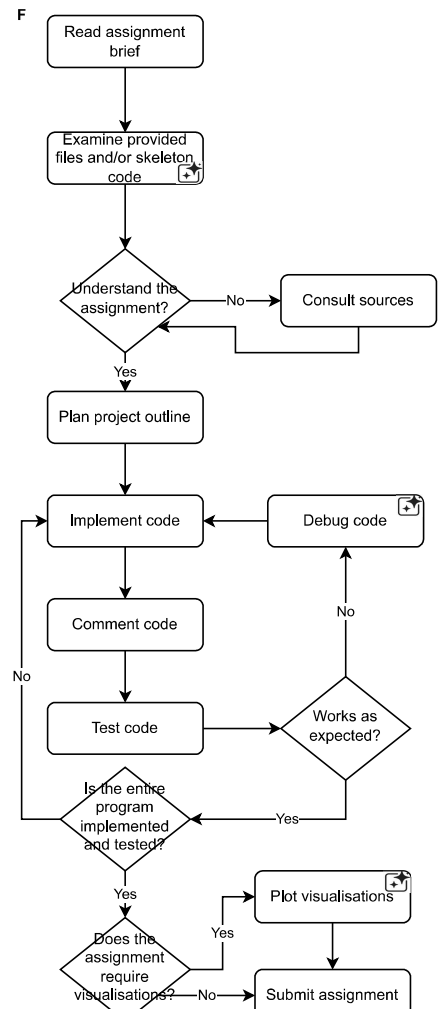
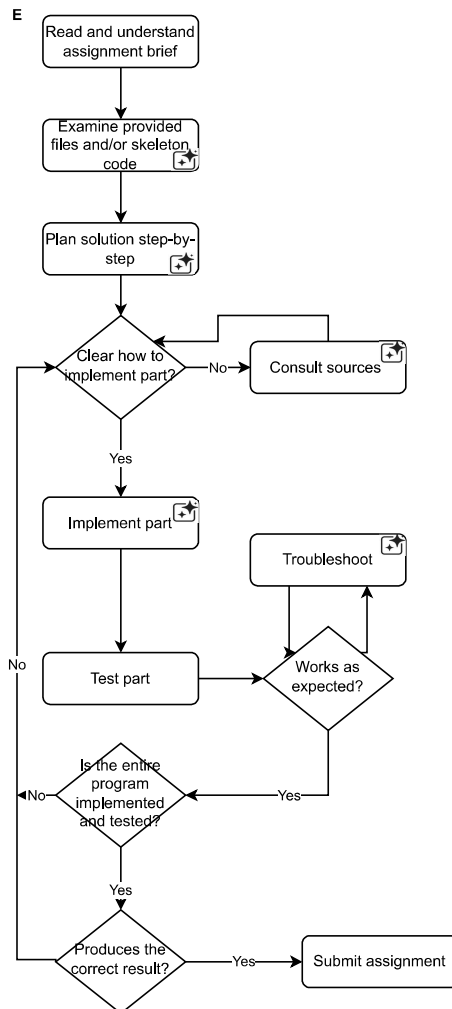
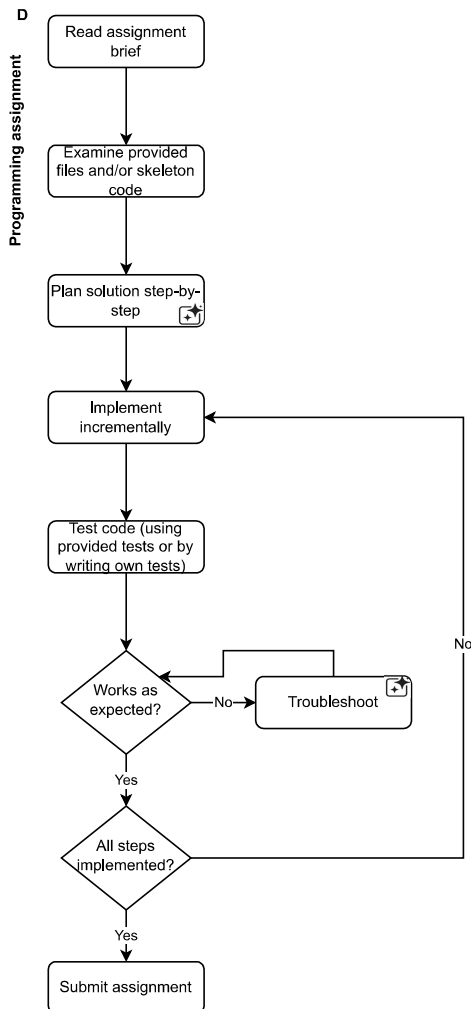
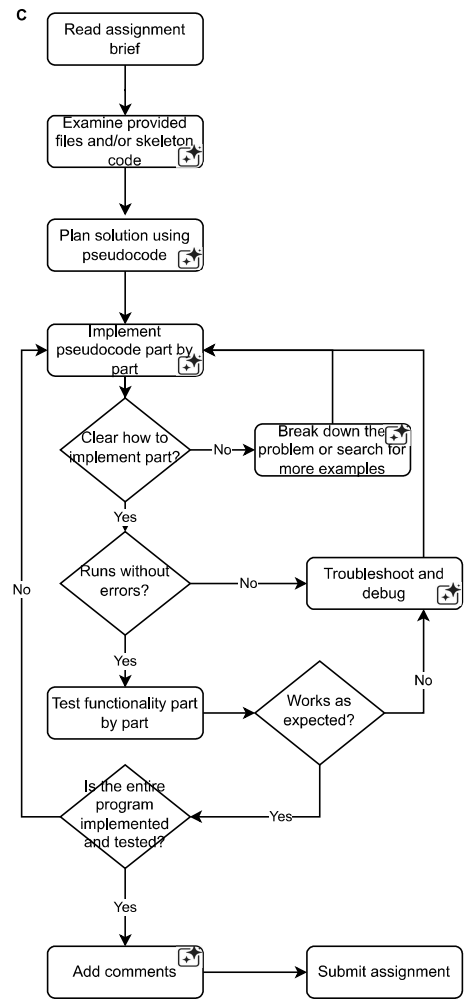
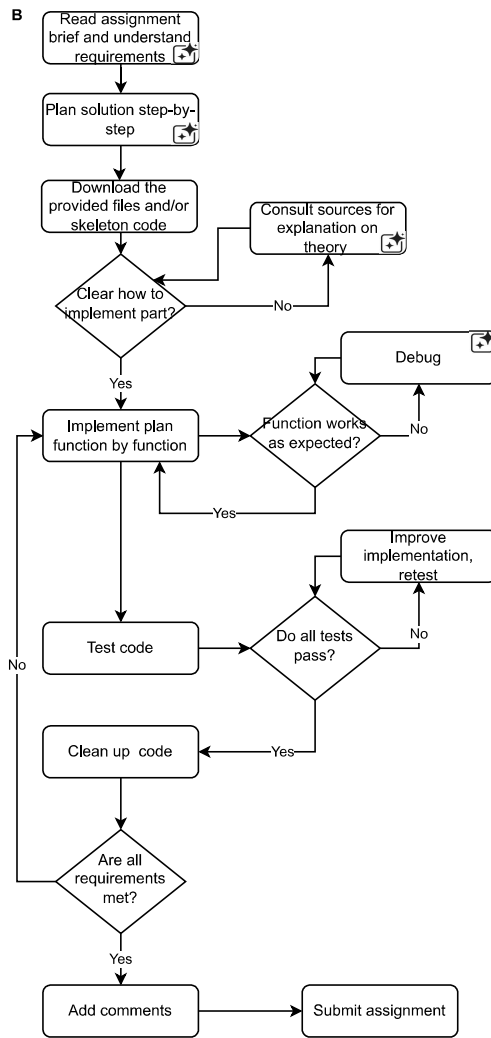
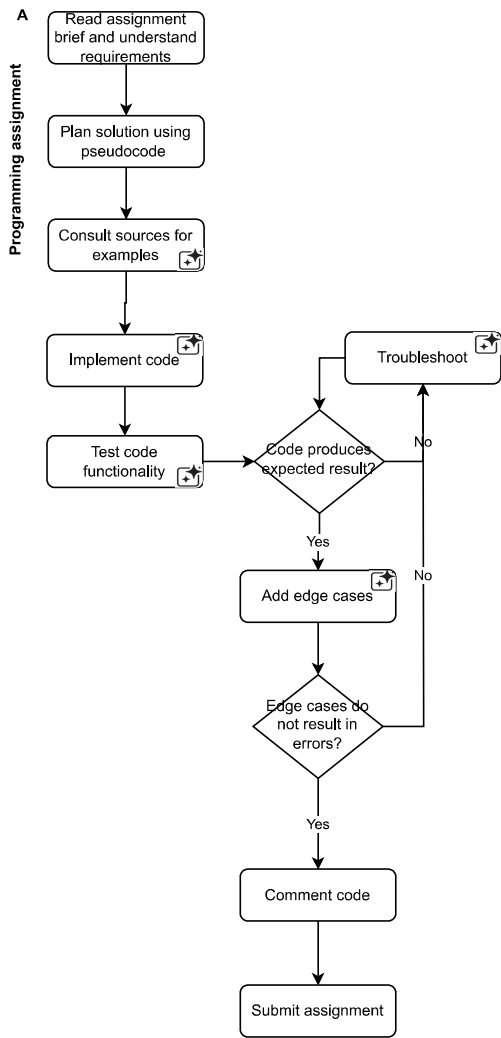
- Zijn er nog dingen die je wil toevoegen?
- Heel erg bedankt voor je deelname.

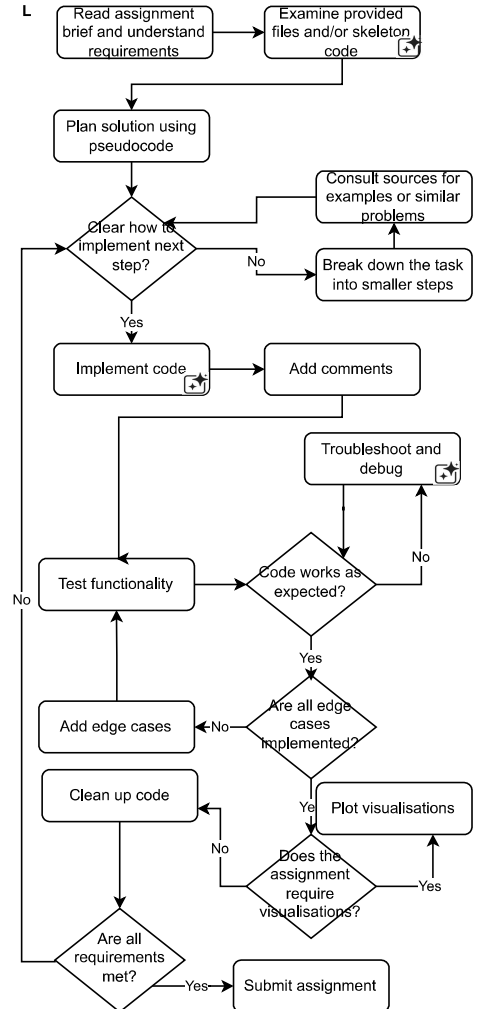
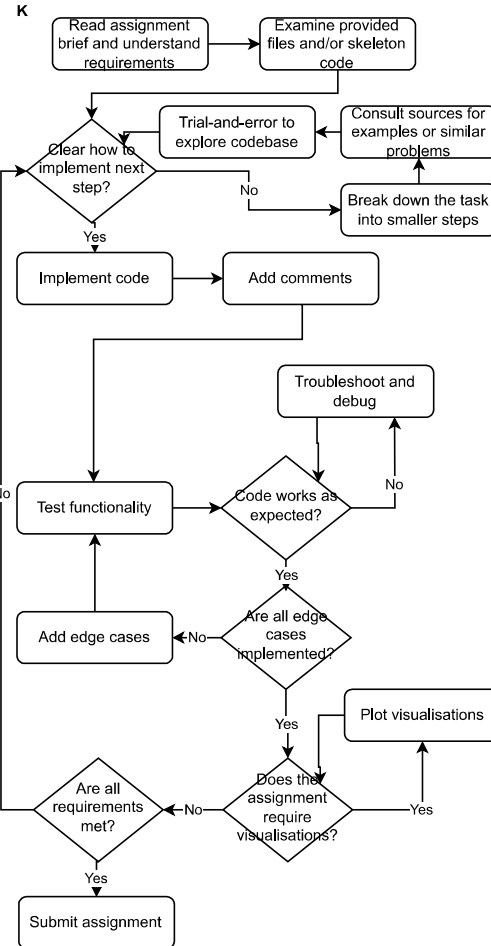
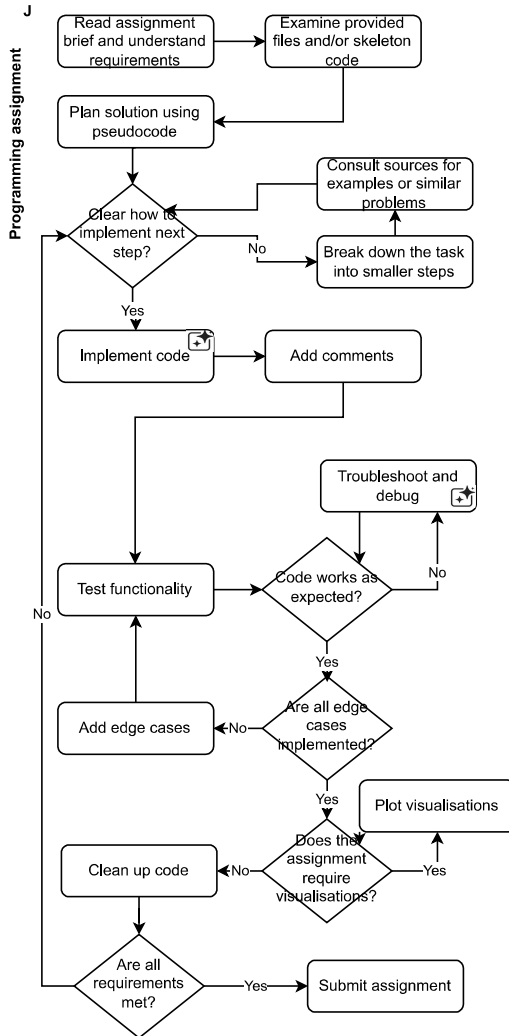
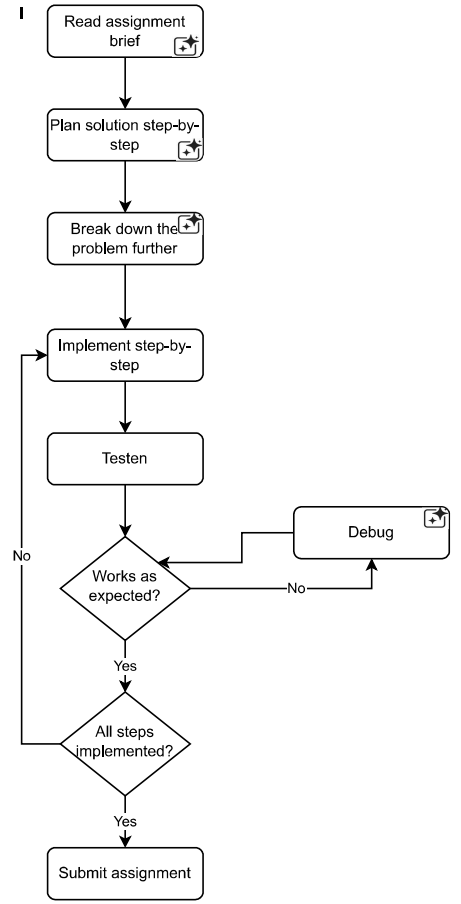
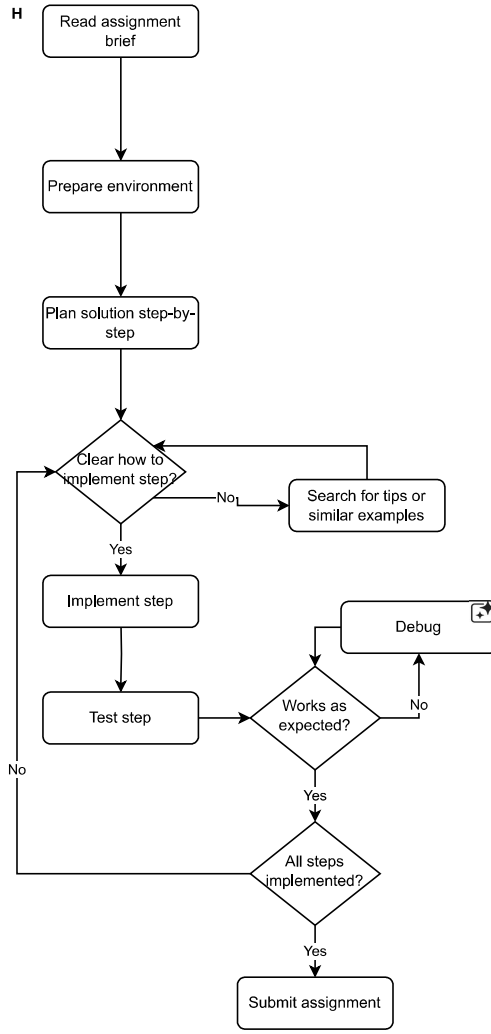
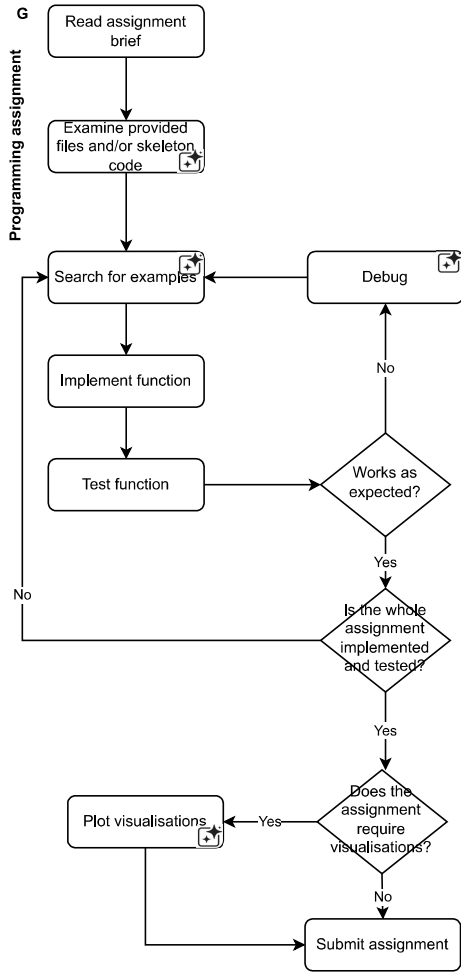
Appendix C

Student Workflows

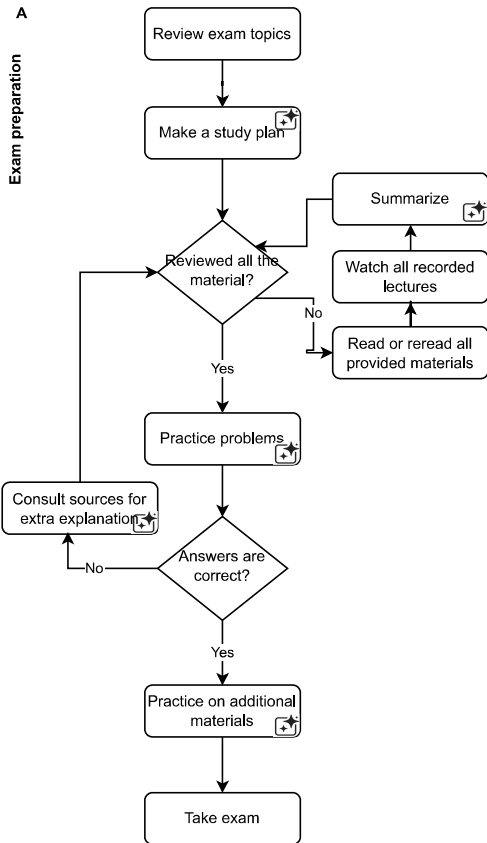




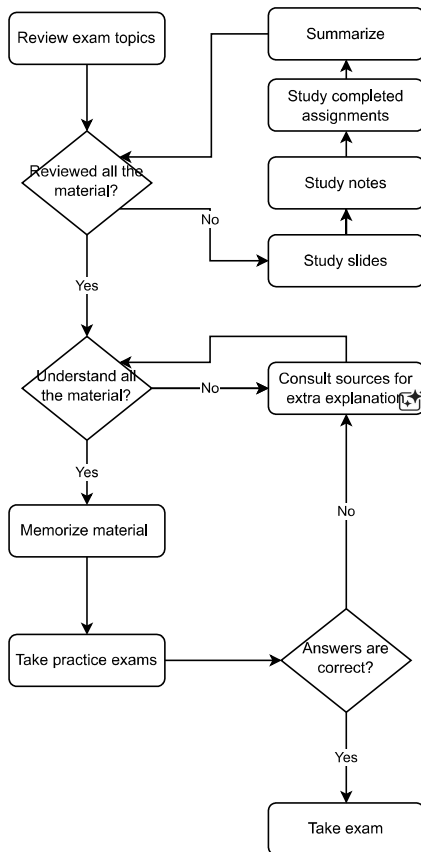




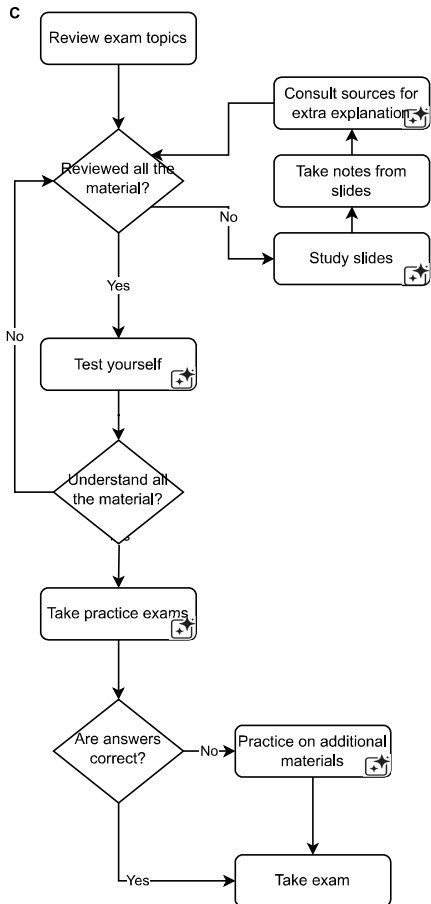
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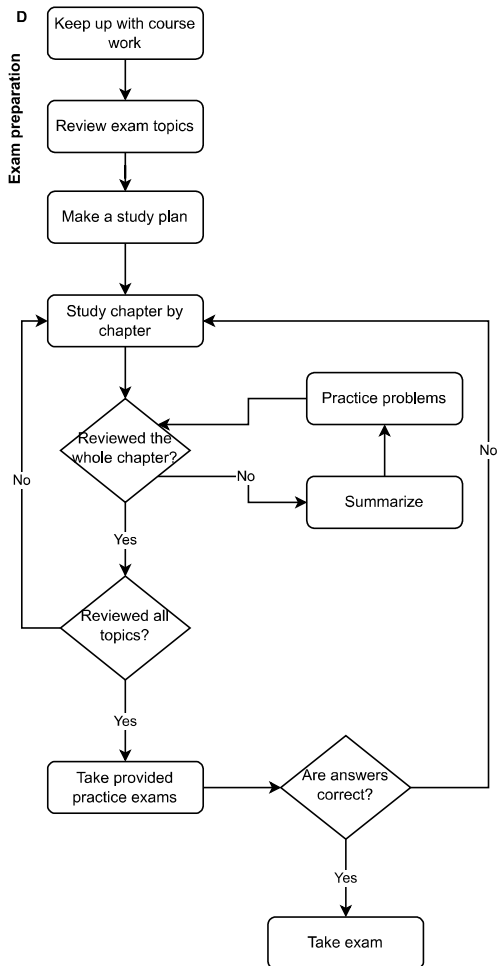
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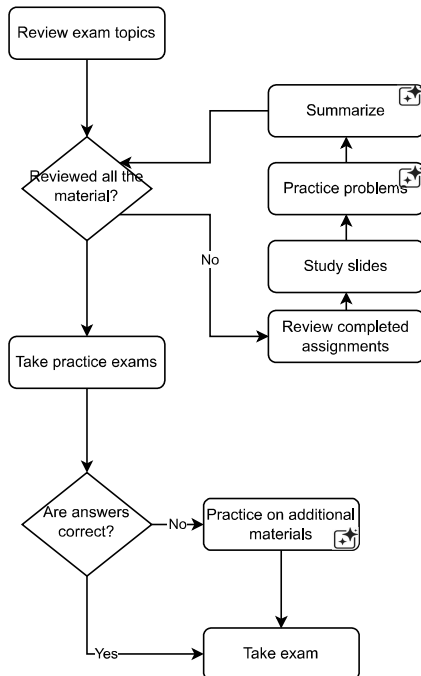
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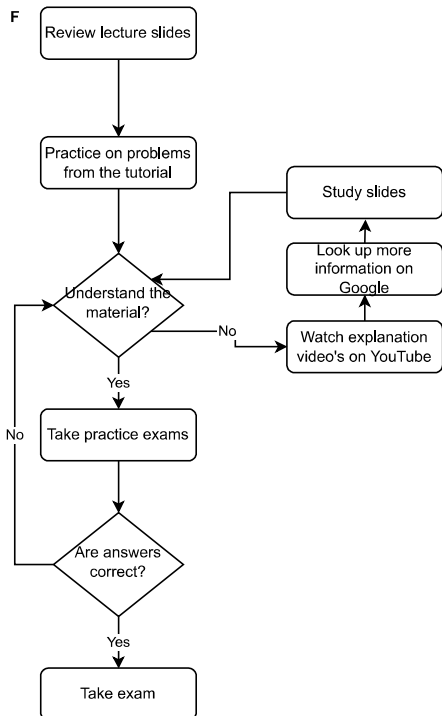
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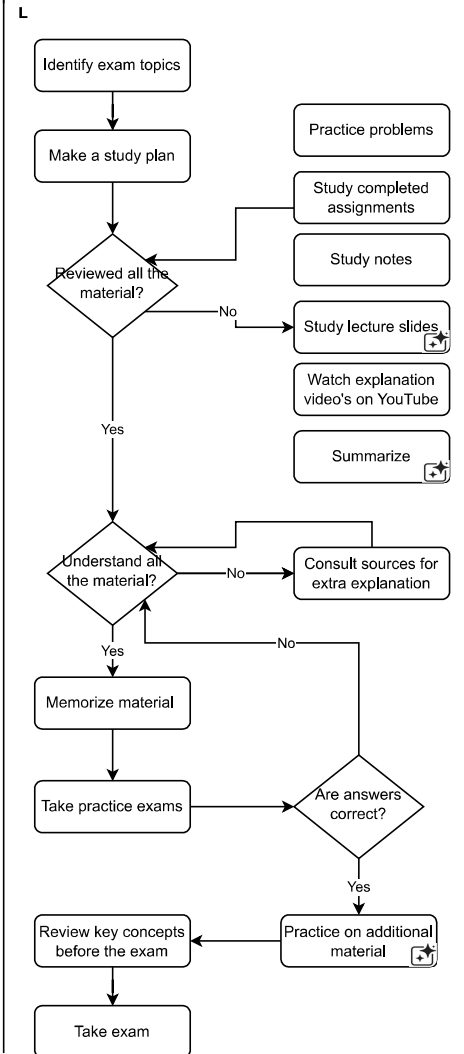
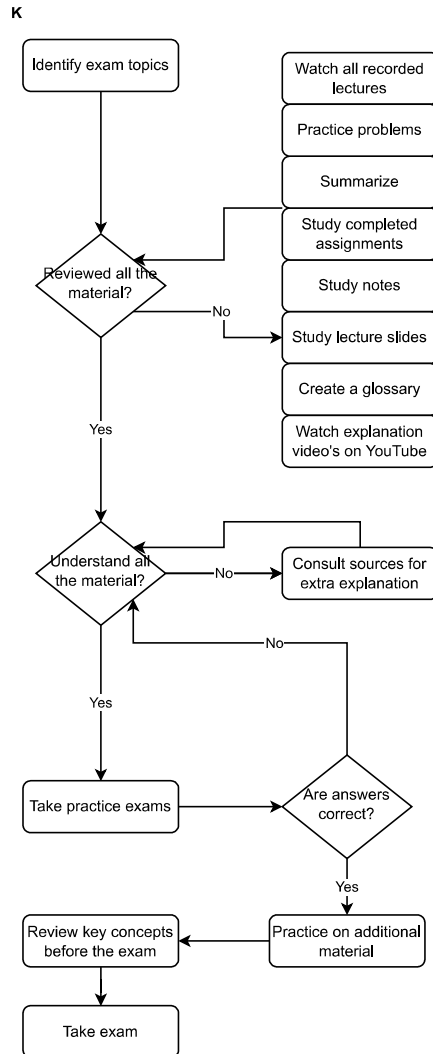
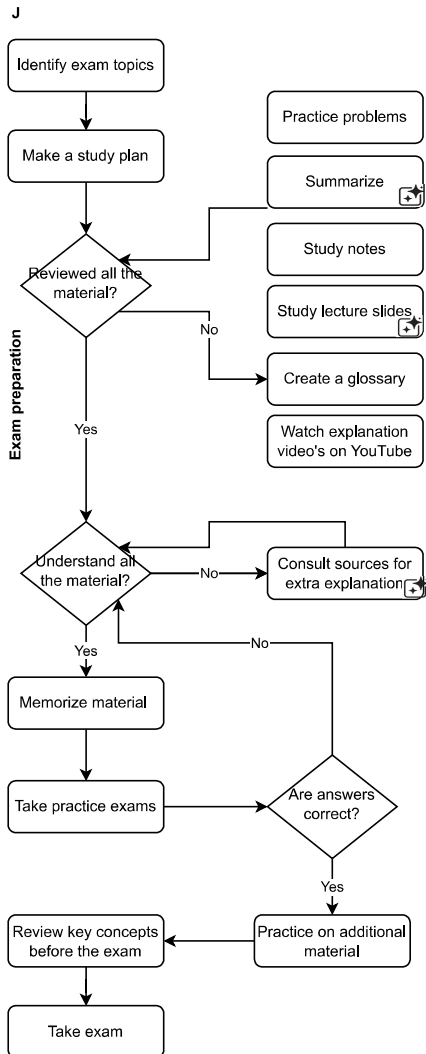
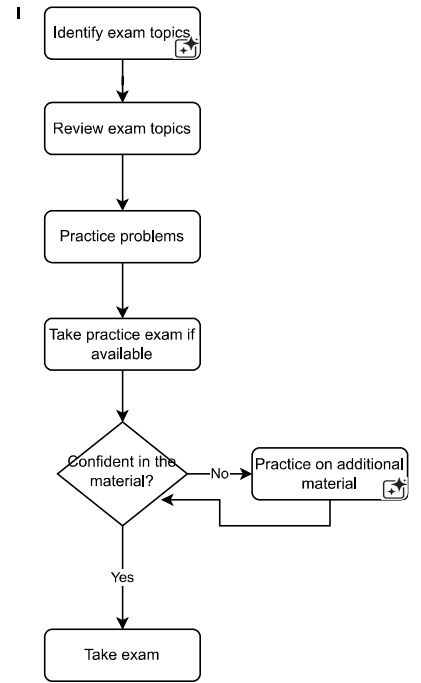
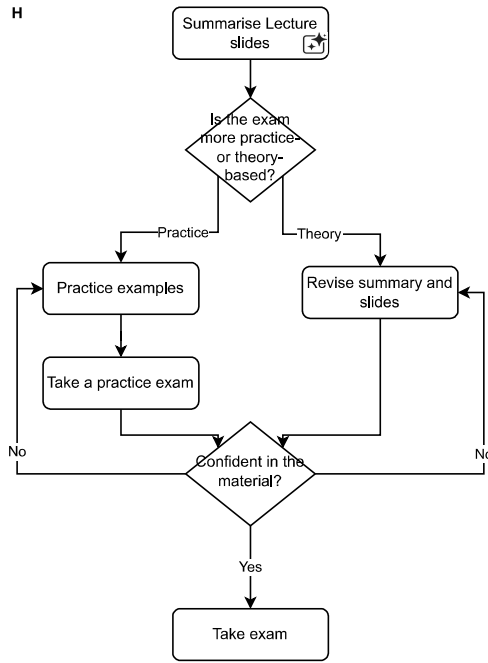
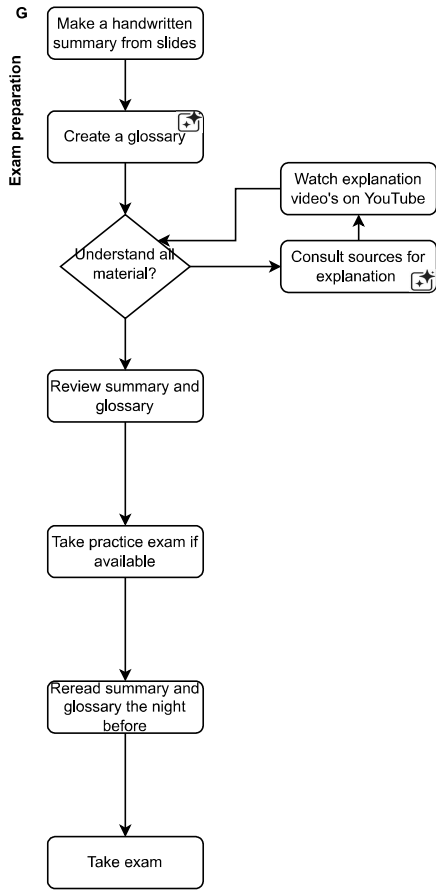


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Appendix D

Survey

Student use of generative AI in academic work

Start of Block: Introduction

Text / Graphic My name is Emma Visser, and I am a third-year BSc Computer Science and Economics student at Leiden University. This survey is part of my thesis research on how **Computer Science students** use Generative AI (GenAI) tools in their studies, and how these tools may influence the way students learn. By GenAI tools, I mean tools like ChatGPT, NotebookLM, or similar applications that can independently generate content such as text, code, audio, or images. The survey will take about **5 to 10 minutes** to complete. Your responses are anonymous and confidential. No personal data is collected. Participation is voluntary, and you can stop anytime. By continuing, you consent to your answers being used for academic research in this thesis. If you have any questions about the survey or my research, feel free to contact me at e.f.visser.2@umail.leidenuniv.nl. Thank you in advance for your time and valuable input! Emma Visser

Text / Graphic This section asks a few short questions about your background to help contextualise your responses.

Q1 Please select your current study programme

- ☐ BSc Computer Science (4)
 - ☐ BSc Data Science and Artificial Intelligence (5)
 - ☐ BSc Computer Science and Economics (6)
 - ☐ BSc Computer Science and Mathematics (10)
 - ☐ MSc Computer Science (7)
 - ☐ MSc ICT in Business and the Public Sector (8)
-

Q2 What is your current year of study?

- ☐ 1st year (1)
 - ☐ 2nd year (2)
 - ☐ 3rd year (3)
 - ☐ 4th year or higher (4)
 - ☐ 1st year master's student (5)
 - ☐ 2nd year master's student (7)
-

Q3 How would you rate your general familiarity with Generative AI tools (e.g. ChatGPT, NotebookLM, Gemini)?

- ☐ Very unfamiliar (1)
- ☐ Somewhat unfamiliar (2)
- ☐ Neutral (3)
- ☐ Somewhat familiar (4)
- ☐ Very familiar (5)

End of Block: Introduction

Start of Block: Written + Programming Assignments - intro

Text The following questions walk through common steps in completing academic assignments, including both **written assignments** (e.g., essays, reports, project papers) and **programming assignments** (e.g., coding tasks for courses or projects). For each step, you'll first be asked how often (if at all) you do the task, followed by how often (if at all) you use GenAI during that step.

End of Block: Written + Programming Assignments - intro

Start of Block: Written + Programming Assignments - Loop



Q4 How often do you perform this step when working on an assignment? *#{lm://Field/1}*
#{lm://Field/2}

- ☐ Never (1)
- ☐ Sometimes (2)
- ☐ About half of the time (3)
- ☐ Most of the time (4)
- ☐ Always (5)

Page Break

Display this question:

If Loop current: Q4 != Never

JS

Q5 Do you use Generative AI (e.g., ChatGPT, NotebookLM) during this step?

$\text{\$}\{Im://Field/1\}$ $\text{\$}\{Im://Field/2\}$

- ☐ Never (1)
- ☐ Sometimes (2)
- ☐ About half of the time (3)
- ☐ Most of the time (4)
- ☐ Always (5)

End of Block: Written + Programming Assignments - Loop

Start of Block: Exam preparation - intro

Text The following questions walk through common steps in **preparing for exams**. For each step, you'll first be asked how often (if at all) you do the task, followed by how often (if at all) you use GenAI during that step.

End of Block: Exam preparation - intro

Start of Block: Exam preparation - Loop

JS

Q6 How often do you perform this step when preparing for an exam? *\${Im://Field/1} \${Im://Field/2}*

- ☐ Never (1)
- ☐ Sometimes (2)
- ☐ About half of the time (3)
- ☐ Most of the time (4)
- ☐ Always (5)

Page Break

Display this question:

If Loop current: Q6 != Never

JS

Q7 Do you use Generative AI (e.g., ChatGPT, NotebookLM) during this step?

Im://Field/1 *Im://Field/2*

- ☐ Never (1)
- ☐ Sometimes (2)
- ☐ About half of the time (3)
- ☐ Most of the time (4)
- ☐ Always (5)

End of Block: Exam preparation - Loop

Start of Block: Attitudes

Text The following questions explore your motivation and attitude toward using GenAI tools in your academic work. Your response will help us understand the different ways students perceive the value of GenAI and what drives their decision to use (or not use) these tools in their studies.

Q8 Which of the below, if any, are reasons which make you **more likely** to use GenAI tools for your studies?

- ☐ To save me time (1)
 - ☐ To improve the quality of my work (2)
 - ☐ To get instant support (3)
 - ☐ To get personalised support (4)
 - ☐ To get support outside of traditional study hours (5)
 - ☐ To improve my GenAI skills (6)
 - ☐ I learn more if I use GenAI than if I don't (7)
 - ☐ Because other students use GenAI (8)
 - ☐ The university encourages me to use GenAI (9)
 - ☐ Nothing: I have no interest in using GenAI tools (10)
-

Q9 Which of the below, if any, are reasons which make you **less likely** to use GenAI tools for your studies?

- ☐ Being accused of cheating by the university (1)
- ☐ Getting false results / hallucinations (2)
- ☐ Getting biased results (3)
- ☐ The university discourages or bans the use of GenAI (4)
- ☐ Not enough is done to protect my data privacy (5)
- ☐ It is not fair to other students who do not use GenAI (6)
- ☐ Tools are too expensive (7)
- ☐ I will learn more if I do not use GenAI (8)
- ☐ The use of data to train GenAI models without the authors' consent (9)
- ☐ The environmental impact (10)
- ☐ Nothing: I am fully comfortable using GenAI tools (11)

End of Block: Attitudes

Start of Block: Engagement

Text The following questions explore how students interact with Generative AI (GenAI) tools when working on academic tasks. Your response will help us understand the nature of engagement with GenAI tools, and how they are integrated into students' learning processes.

Q10 How actively do you engage with the output from GenAI tools? Select the option that best describes your typical use.

- ☐ I copy the output with little or no changes (1)
 - ☐ I adapt the output significantly to fit my needs (2)
 - ☐ I use the output as inspiration but write/code everything myself (3)
 - ☐ I only use GenAI to check or review my own work (4)
 - ☐ I don't use GenAI tools (5)
-

Q11 How often do the GenAI tools you use produce hallucinations?

- ☐ I do not know (6)
- ☐ Never (1)
- ☐ Sometimes (2)
- ☐ About half of the time (3)
- ☐ Most of the time (4)
- ☐ Always (5)

End of Block: Engagement

Start of Block: Disclosure

Text The following questions focus on how often students disclose their use of these tools, and what factors influence their decision to do so or not. Your response will help us better understand current practices and perceptions around transparency and academic integrity in the context of GenAI.

Q12 How often do you disclose the use of GenAI tools in your academic assignments?

- ☐ Never (1)
 - ☐ Sometimes (2)
 - ☐ About half the time (3)
 - ☐ Most of the time (4)
 - ☐ Always (5)
-

Q13 Which of the following, if any, are reasons that make you **more likely** to disclose the use of GenAI tools in your studies?

- ☐ I use the output exactly or with minimal changes (1)
 - ☐ I rely heavily on the GenAI tool to complete the task (2)
 - ☐ I believe in academic honesty and transparency (3)
 - ☐ I am explicitly asked to disclose it (4)
 - ☐ There are clear guidelines on how to disclose from the university (5)
 - ☐ I want to avoid potential issues with plagiarism or misconduct (6)
 - ☐ Other (please specify): (7)
-

Q14 Which of the below, if any, are reasons which make you **less likely** to disclose the use of GenAI tools for your studies?

- ☐ I don't think it is necessary if I adapt the output (2)
 - ☐ I believe there is a taboo around using GenAI tools (3)
 - ☐ I think it is similar to using other online resources (4)
 - ☐ I could have come up with the same output myself (5)
 - ☐ Coding often involves reusing code from the internet anyway (6)
 - ☐ I am afraid of being penalised (7)
 - ☐ There are no clear guidelines on how to disclose from the university (8)
 - ☐ Other (please specify: (9)
-

End of Block: Disclosure
