"We Need to Analyze Students GenAI Use": Towards an AI Adoption Framework for Higher Education

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Abstract: *Context:* Generative AI (GenAI) tools such as ChatGPT are rapidly transforming how students learn and work. While adoption among learners is high, institutional frameworks in higher education often lag behind. *Objective:* This study pursues two primary objectives: 1) identifying students' use-cases for GenAI, and 2) synthesizing these into a systematic description how to integrate GenAI into higher education. *Method:* To address these objectives, we conducted a case study at the University of Applied Sciences and Arts Hannover. We used a questionnaire that included both quantitative and qualitative questions. *Results:* Our findings reveal that 129 (n=151) of the students use GenAI tools in their studies. Based on a synthesis of the results, we created a systematic description for GenAI integration into higher education. *Contributions:* We offer specific solutions: with the AI Adoption Framework, higher education institutions will be able to review and adapt their regulations and curricula in relation to GenAI to keep up with the pace of change in the field.

1 INTRODUCTION

The increasing availability and advancement of generative artificial intelligence (GenAI) have led to significant transformations across various domains, including higher education (Neumann et al., 2023). Among the different branches of AI, GenAI tools have gained interest due to their ability to generate human-like text, images, code, and other forms of content (Freise et al., 2025; Jimenez et al., 2024; Rüdian et al., 2025; Shailendra et al., 2024). These tools, such as ChatGPT by OpenAI, have introduced new opportunities and challenges in higher education and are available by the general public (Grashoff et al., 2024; Rasheed et al., 2025; Sami et al., 2025; Zhang et al., 2024), particularly in disciplines that involve substantial amounts of written assignments, research, and problem-solving (Speth et al., 2024). In the context of higher education, students from diverse disciplines are increasingly integrating GenAI tools into their workflows (von Garrel et al., 2023). The rapid adoption of these tools has sparked discussions regarding their potential benefits and risks in academia. While some educators perceive them as valuable aid in improving learning efficiency and fostering creativity, others raise concerns about ethical implications, the authenticity of academic work, and potential misuse of plagiarism or academic dishonesty (Chen et al., 2020).

Nowadays, higher education is challenged by several disruptive events of the last decade (Schön et al., 2023). In addition to the challenges due to the GenAI era outlined above, the Covid-19 pandemic is a good example. The widespread shift to online and/or distance learning during the Covid-19 pandemic has led to a major digital transformation, as universities around the world have adopted various tools for remote working and teaching, used virtual tutoring systems, or moved to cloud repositories that provide lecture materials over distance (Matthies et al., 2022; Neumann et al., 2022).

Despite the pandemic, we see today new and upcoming challenges at an accelerating pace as we move towards an AI-driven era (Förster et al., 2024; Schön et al., 2023). Students with a stronger computer science focus like information science or e-government are leveraging these technologies for

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tasks such as requirements engineering (Brockenbrough and Salinas, 2024), code generation (Maher et al., 2023; Savelka et al., 2023; Speth et al., 2023), report writing (Datta, 2024), and summarizing complex concepts (Speth et al., 2024). However, despite the growing use of GenAI tools, the extent to which students rely on these tools, as well as the nature of their specific applications, remains under-explored (Zastudil et al., 2023). Additionally, institutional policies on AI usage in academia are still evolving, leading to uncertainties among students regarding acceptable AI-assisted practices in their studies (Nithithanatchinnapat et al., 2024).

Given the profound potential of GenAI in higher education, it is crucial to examine how students utilize these tools (Neumann et al., 2023), identify the perceived benefits and challenges, and understand their implications for academic integrity as well as learning outcomes (Chan et al., 2023).

In this paper, we aim to bridge the existing research gap by examining the adoption and impact of GenAI tools among students. Furthermore, we see a lack in developing the curricula of the study programs for the needed skills in the future. Thus, the above motivates the following research questions:

- **RQ 1:** How do students utilize GenAI tools in their studies?
  With RQ 1, we gain an in-depth understanding of how students use GenAI tools in their studies. We focus strongly on the computer science-related fields of business information systems and E-Government in one German instituion to minimize biases of different academic fields and their particularities (*e.g.,* skill-sets).
- **RQ 2:** How can institutions systematically adapt their regulations and curricula with regard to GenAI through a structured framework?
  Using insights from RQ 1, we have created a framework to systematize our findings and provide universities with a tool to refine their curricula and adapt degree program regulations for GenAI usage.

Based on the findings of our case study, we present the main contribution of this paper: A framework to adopt GenAI into their study program curricula and regulations. To be precise in wording, we understand a *framework* in this paper as a systematic described theoretical approach, which is in line with existing literature (Lederman and Lederman, 2015).

The remainder of this paper is structured as follows: Section 2 reviews related work on GenAI in education, focusing on existing studies that have explored its adoption, benefits, and challenges. Section 3 outlines the research design, detailing the methodology, data collection process, and analytical approach. Section 4 presents the key findings derived from the survey, followed by Section 5, which discusses the implications of the results for students, educators, and institutional policies. Section 6 addresses the study's limitations, and Section 7 concludes the paper with a summary of findings and directions for future research.

2 RELATED WORK

We searched for primary studies dealing with GenAI adoption in the Higher Educational Context. First, we focused on existing frameworks for GenAI adoption. (Shailendra et al., 2024) propose a *4E framework* (Embrace, Enable, Experiment, Exploit) to systematically integrate GenAI into higher education. The iterative designed framework addresses curriculum design, roles of stakeholders, training requirements, ethical considerations, and evaluation mechanisms. Challenges such as academic integrity, privacy, and assessment fairness are also recognized. However, the framework has its limitations, especially in terms of detailed methodological guidance and empirical validation. Furthermore, there is a lack of explicit strategies for addressing potential technological biases or inaccuracies (*e.g.,* data hallucination).

Additionally, (Su and Yang, 2023) introduced the *IDEE framework* that consists of four steps. They include, *e.g.,* outcomes identification, as well as an application example from practice. Though the framework is introduced on a level of detail, the practical application lacks on specific measures and actions.

(Southworth et al., 2023) present the *AI iteracy model* aiming to provide an opportunity for a systematic curriculum development of AI courses for undergraduate study programs. The framework consists of five steps and is designed as an iterative approach. Even if this frameworks has its strengths in curriculum development, several other important facets such as the focus on regulations are lacking.

To sump up, all of the identified models are multi-step frameworks, mostly applying an iterative approach aiming to provide a solution for the ongoing development of new or updated GenAI tools and technologies. However, all of the existing models are lacking on specific aspects such as artifacts and thus, do not provide an opportunity for us to apply them at our universities. Besides the strong focus on AI courses ((Southworth et al., 2023)) the identified frameworks are mostly to detailed and heavyweight for an application on specific study programs. The main limitation of these frameworks is their failure to

consider the specific circumstances at higher education institution. Specifically, they often overlook how students are currently using GenAI tools and the existing state of curricula and regulations. Consequently, we opted to develop our own data-driven framework.

In addition to the frameworks presented in the literature, we also found studies focusing on students' use of GenAI tools. Several empirical studies have examined how students engage with AI-driven tools, their frequency of use, and associated benefits and challenges. Research from University of Applied Sciences Darmstadt (von Garrel et al., 2023) investigated the frequency and application of generative AI tools among university students across disciplines. The findings suggested that GenAI tools were predominantly used for text generation, summarization, and code development. The nationwide applied survey was conducted in Germany in 2023 and focused on student engagement with ChatGPT and similar GenAI tools. The study revealed that approximately 63.4% of the surveyed students utilized generative AI tools for academic purposes, with significant variations depending on the field of study. Another study ((Gottschling et al., 2024)) explored the implications of AI usage in student learning environments, highlighting the ethical concerns and academic integrity issues associated with AI-generated content.

Existing surveys aimed at thoroughly investigating and understanding students' application and use of GenAI tools are limited, particularly as they mostly include data from disciplines other than computer science. Therefore, we decided to design and conduct our own survey tailored specifically to this context. A detailed explanation of the applied research design is provided in the next section. Moreover, these studies have identified varying degrees of student awareness regarding institutional AI regulations. Some universities have established clear policies, whereas others are still in the process of defining guidelines. This discrepancy influences how students perceive and utilize AI tools in their coursework, underscoring the need for more structured institutional frameworks.

3 RESEARCH DESIGN

Our research questions focus on two main areas: First, the specific GenAI tools students use, their application areas, and how institutional guidelines influence their adoption. Second, we aim to develop a framework to facilitate adoption of GenAI within higher educational institutions. To address these research questions, we designed a case study according to the guideline by ((Yin, 2009)) at the University of Applied Sciences and Arts Hannover focusing on the specific discipline of information systems. Figure 1 depicts the research design including the applied research methods.

3.1 Case Context

The University of Applied Sciences and Arts Hannover is located in Germany offering education in a wide span of disciplines such as design, engineering, economics, and computer science. In total, around 10,000 students are enrolled in the different programs in five faculties which are located over the city of Hannover. Our case study focus on the information systems discipline. The Department of Business Information Systems (Faculty IV) organizes and offers three different study programs for both a bachelor's and a master's degree. Here, we took the bachelor programs **B**usiness **I**nformation **S**ystems (BIS) and **E-Gov**ernment (EGOV) under study. In winter term 2024-2025 there were 465 of BIS students and 115 of EGOV students enrolled. A detailed overview per term is given in Table 1.

The department is incorporating GenAI across different aspects of its study programs. Shortly after the launch of ChatGPT in November 2022, a working group in the department analyzed the opportunities and risks to adapt regulations and the impact on several exam types. Based on these analysis results, the university adopted specific GenAI related aspects to their regulations, especially for the bachelor thesis and written exams. For instance, students have to respect guidelines for theses and writing exams. These guidelines provide specific regulations related to the format (*e.g.,* font, size, and line spacing), the citation style(s), and detailed information regarding the use of tools, including GenAI. By explicitly addressing GenAI, the guidelines aim to implicitly integrate this technology into the study programs. The last core adaption of the curriculum of both study programs dates back to 2018 and thus, the curricula do not define GenAI skills or further measures explicitly. However, in various courses in both study programs lecturers provide GenAI integration to the students. Examples are Requirements Engineering, Research Methods & Scientific Writing, or Math.

3.2 Data Collection & Analysis

Questionnaire Design: We used an online survey as the primary data collection instrument. The choice of this method was driven by the need to obtain a broad and representative sample of students from the targeted disciplines at the case institution. The ques-

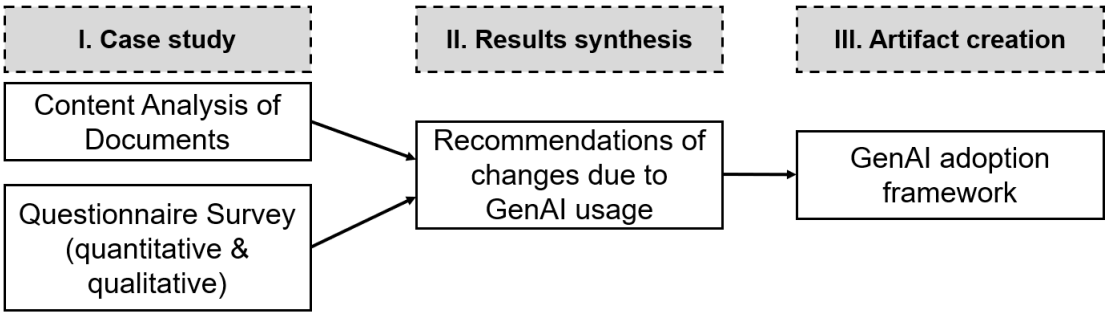

Figure 1: Research Design.

tionnaire was divided into four main parts. The questionnaire can be found at Zenodo ((Bischof et al., 2024)). The first part focused on demographic information, gathering details such as the study program. This information allowed for the categorization of responses and ensured that only relevant data from BIS and EGOV students were included in the analysis.

The second part explored students' attitudes toward GenAI tools. It assessed their familiarity with AI-based applications, their perceived usefulness, and their awareness of university policies concerning AI use. Responses in this part were recorded using a 5-point Likert scale, ranging from "*strongly disagree*" to "*strongly agree*", allowing for a nuanced understanding of student perspectives.

The third part investigated usage patterns and policy compliance, asking students whether they used GenAI tools and, if so, which ones. It also inquired about their primary use cases, such as assisting with research, programming, summarizing academic texts, or preparing for exams. Additionally, this part assessed whether students believed their AI usage aligned with university guidelines, which provided insight into potential gaps in institutional communication regarding AI regulations.

The final part covered perceived benefits and challenges associated with the use of GenAI in academic settings. While most of the questionnaire employed structured, multiple-choice questions, this part also included open-ended questions. This allowed students to elaborate on their experiences, including specific advantages and difficulties they encountered while integrating AI tools into their learning process.

Data Collection and Sampling Strategy: Conducted between November 5, 2024, and December 31, 2024, the survey was hosted on LimeSurvey. Participation was entirely voluntary and anonymous to mitigate social desirability bias and ensure compliance with ethical standards related to student privacy.

To enhance the reliability of the data, the survey underwent a pilot phase involving 20 students from BIS and EGOV. Their feedback contributed to refining the questionnaire by improving clarity, ease of understanding, and the structure of the response format. Adjustments made after the pilot phase included rewording complex questions and modifying the layout for better readability.

The survey was distributed through multiple communication channels to maximize participation. Lecturers promoted the study in relevant courses, and QR codes linking to the survey were displayed in classrooms. Additionally, students received direct invitations via email and online university portals, ensuring that the target audience was adequately reached.

A non-probabilistic sampling approach was employed, meaning that students chose to participate voluntarily rather than being selected through a randomized process. While this method facilitated efficient data collection, it also introduced potential bias, as students with an interest in AI might have been more inclined to respond.

Data Analysis: The final data set ($N = 151$) was reviewed and only includes fully completed submissions. The analysis was conducted using statistical software to ensure accurate processing. The dataset was cleaned and managed using Python's Pandas library, while Matplotlib and Seaborn were used for visualizing trends. Further statistical computations, such as confidence intervals and significance testing, were performed using SciPy to verify the reliability of the findings.

The multiple-choice responses were analyzed quantitatively, with frequency distributions and comparative analyses conducted to identify patterns in GenAI tool adoption across different student groups. Open-ended responses were processed using a thematic analysis approach (according to (Cruzes and Dyba, 2011)), in which recurring themes related to the benefits and challenges of AI adoption were categorized and interpreted.

Table 1: Number of students by term and study program.

Term	BIS	EGOV	Total Count
1	33	13	46
2	16	2	18
3	19	20	39
4	5	0	5
5	7	17	24
6	6	0	6
7	4	6	10
8	3	0	3
Overall Total	93	58	151

Sample Description: A total of 151 students participated in the survey, all of whom were enrolled at the case university. The sample consisted of 93 BIS (61.59%) and 58 EGOV students (38.41%). The sample distribution reflects the general student composition of these programs, although students in term 5 were underrepresented due to external internships during the survey period. Table 1 provides an overview of the students enrolled per term and study program.

In terms of academic level, most participants were in their first to fourth term, while students from the fifth and seventh terms were significantly less represented. This is attributed to their participation in off-campus practical training phases, which limited their engagement with university-related activities. However, keeping the total count of enrolled students in both programs in mind, we have a statistical significant sample for both program (for BIS: 93 out of 465 or 20%; for EGOV: 58 out of 115 or around 50%).

Ethical Considerations: To maintain ethical integrity, strict measures were implemented throughout the research process. Participation was fully voluntary, and students had the opportunity to withdraw at any stage without justifying. The survey was entirely anonymous, ensuring that no personal identifiers were collected. Additionally, formal approval from the university was obtained before data collection, ensuring that the study adhered to ethical research guidelines.

Synthesis and Framework Creation: We analyzed questionnaire data alongside institutional documents to examine the use of GenAI tools, focusing particularly on students' use-cases and existing regulations governing their permitted usage.

Based on a thorough analysis of our datasets, we first synthesized our findings. We then discussed which recommendations for GenAI adoption could be identified. In a second step, considering the relationships among these recommendations, we developed a framework and elevated our approach for the selected case to a meta-level, aiming to provide a solution applicable to other academic institutions.

4 RESULTS & DISCUSSION

Here, we answer our first research questions aiming to provide in-depth findings as a basis for the next section in which we will present our AI adoption framework for higher educational contexts.

4.1 GenAI Adoption by Students

First, we present the answer of RQ 1: *How do students utilize GenAI tools in their studies?*

One of the key findings of this study is the high adoption rate of GenAI tools among students. Of the 151 students surveyed, 129 students (85.43%) reported that they actively use GenAI tools in their studies. Conversely, 19 students (12.58%) indicated that they do not use these tools, while 3 students (1.99%) abstained from answering. A breakdown of usage by study program reveals that 88.17% of BIS students and 81.03% of EGOV students use GenAI. This suggests that AI adoption is slightly higher among BIS students, possibly due to the stronger emphasis on computer science discipline and specific courses for programming and data-driven applications.

GenAI tools used by students: Among the students who use GenAI, ChatGPT is by far the most frequently used tool, with 93.8% of whom use it regularly. Other tools, such as Google Bard and DeepL Write, were mentioned but to a much lesser extent. The widespread preference for ChatGPT may be due to its intuitive user interface, availability, and broad range of functionalities. Additionally, students in computer science-related fields may favor ChatGPT over other AI tools due to its strong capabilities in code generation and debugging.

When asked about paid AI subscriptions, the vast majority of the AI-using respondents (85.27%) reported that they rely exclusively on free versions of AI tools. Only 19 students (14.73%) indicated that they use paid AI services, citing greater functionality and improved response accuracy as their primary reasons.

Use Cases of GenAI in Academic Work: Students use GenAI tools for a variety of academic tasks, with the most common applications being:

- Research Assistance (40.15%): AI is frequently used to summarize academic papers, generate explanations, and structure research topics.
- Programming Support (37.8%): A large percentage of students, particularly from BIS, use GenAI for coding help, debugging, and generating sample code snippets.
- Text Summarization (34.65%): Many students rely on GenAI tools to condense lecture notes, academic papers, and textbooks into more digestible formats.

Other reported applications include exam preparation, language translation, and writing assistance for essays and reports (also known as written exams). However, students also acknowledged that over-reliance on GenAI for academic tasks can limit critical thinking skills and independent problem-solving.

Perceived challenges of GenAI usage by students: A major concern revealed in the survey is the lack of clarity surrounding institutional regulations on AI usage.

The majority of students, regardless of most academic terms (with the exception of term 6), report that existing regulations are unknown to them. We initially expected that the number of students familiar with the regulations would steadily increase with each semester, while the number of those unaware of them would decrease accordingly. However, the data suggest that a significant degree of uncertainty regarding existing rules and regulations persists until the end of the study program. Consequently, we investigated the extent to which students believe their use of GenAI adheres to established guidelines and regulations:

- 43.7% of students were unsure whether their AI usage was compliant with academic policies.
- 37.2% believed their use was aligned with the university's rules.
- 19.1% admitted they might be violating institutional policies.

This high degree of uncertainty highlights a gap in institutional communication, as many students reported a lack of clear AI usage policies from faculty members and university administration. Nevertheless, based on our document screening, we found that the internal university communication rules imply mentioning existing guidelines and regulations. Thus, we also see a lack of specific skills (or motivation) on the student side to verify the existing guidelines for GenAI usage rules. However, one may assume that some students may unknowingly violate academic integrity standards due to unclear or inconsistent enforcement. Furthermore, concerns about over-reliance on GenAI tools were also raised. A significant portion of students warned that relying too heavily on AI can impede their ability to develop a deeper understanding, diminish critical thinking skills, and promote passive learning habits. Furthermore, 12 students explicitly mentioned concerns related to data privacy, particularly regarding the storage and use of personal input data by AI companies.

In conclusion of our findings on the use of GenAI by students, we compared our findings to the results from the existing literature. Here, we focused our comparison to a previous nationwide survey((von Garrel et al., 2023)), which reported that only 63.4% of students in Germany used GenAI. In contrast, our study found a significantly higher GenAI usage rate of 85.43%. A Chi-square test confirmed that this difference is statistically significant (χ^2 = 30.09, p ¡ 4.1×10^{-5}). However, the survey ((von Garrel et al., 2023)) was conducted in 2023 and considered a wide spread of study programs, while ours focused strongly on information systems and related disciplines. Thus, the results discrepancy may be due to the increasing prevalence of GenAI tools over time, or the higher affinity of business informatics and e-government students for GenAI technologies compared to students from other disciplines. Nevertheless, especially universities providing study programs with a relation to computer science, information systems or similar should be aware that GenAI adoption by the mass of their students may be the reality; for our case university it is. Thus, universities should aim to integrate AI literacy into academic programs, ensure clear policy communication, and encourage responsible AI use. By doing so, they can prepare students for an increasingly AI-driven world while preserving the integrity of higher education.

5 GenAI ADOPTION FRAMEWORK FOR HIGHER EDUCATION

The findings of this study underscore the transformative impact of GenAI on higher education. As GenAI tools become increasingly sophisticated, educational institutions must strike a balance between leveraging AI's benefits and maintaining academic integrity. Our case study results suggest that while students readily adopt GenAI, institutional policies have not yet fully adapted to this technological shift. Moving forward,

a proactive and informed approach is essential. Based on a thorough analysis of our findings, we answer our second research question: *How can institutions systematically adapt their regulations and curricula with regard to GenAI through a structured framework?*

Our AI Adoption Framework enables higher education institutions to review and update their regulations and curricula in response to GenAI advancements, ensuring they keep pace with rapid changes in the field. The framework consists of four iterative steps, detailed in the following and illustrated in Figure 2.

I. Document Analysis. The first step comprises a document analysis. When analyzing documents, all internal documents such as examination regulations or guidelines, and curricula, including module descriptions, should be taken into account. It is also useful to consider external documents on the use and functionality of AI tools and models, or general policies such as the EU AI Act, or scientific studies focusing on the discipline should also be included.

II. Survey with quantitative and qualitative items. In the second step, a questionnaire will be developed based on the results of the document analysis. It is a challenge to conduct the survey with a representative number of students. Therefore, we recommend combining the survey with other data sources to obtain comprehensive insights into GenAI usage. Additionally, study programs should be analyzed separately to minimize disciplinary biases, allowing the questionnaire to reflect the specifics of individual programs or subject areas. Furthermore, regular reviews and iterative adjustments of the questionnaire are advisable, especially to account for emerging developments, such as new GenAI models or policy changes.

III. Synthesize findings. Based on the findings of the previous two steps, it is now necessary to synthesize the findings in order to make specific recommendations for the adaptation of internal institutional regulations and/or the curriculum.

IV. Update regulations and curricula. The recommendations developed in this step serve as an authoritative and well-founded basis for the actual updating of internal institutional regulations, guidelines, or even curricula. This usually requires cooperation in committees and organizational units of an academic institution and might be correspondingly time-consuming. This underscores the importance of thoroughly preparing for the update.

After the first run of this described process, the iterative transition back to the first step of the framework takes place (shown in blue in the Figure 2). Given the highly dynamic nature of the GenAI market, we anticipate regular releases of new models and enhancements in functionality. We also expect other vendors to enter the market and present and release optimized GenAI models. This requires a regular review of internal documents and, in particular, external documents, such as new or amended laws, guidelines, and documentation from GenAI providers or scientific findings on the use of GenAI in practice and research. As a result, it can be assumed that the use of GenAI by students will also change regularly, which in turn will lead to recurring surveys. Especially in academic institutions, where changes in curricula and regulations are subject to complex processes, careful preparation of these adjustments is necessary. Our proposed iterative framework can efficiently organize efforts and consistently integrate new findings into the ongoing development of curricula and regulations.

6 LIMITATIONS

As detailed in Section 3, we employed a systematic approach to prepare and conduct our case study. However, all studies have limitations. In this section, we address these limitations using the validity threats concept outlined by Runeson and Hoest (Runeson and Höst, 2009).

Construct Validity. The survey questions may have introduced interpretation bias, particularly regarding terms like "*academic integrity*" and "*rule compliance*", due to the absence of clear university guidelines on GenAI usage. Additionally, self-reported GenAI usage may be inaccurate due to social desirability bias, despite anonymity. The framing of questions, including specific GenAI tool examples, may have led to an anchoring effect, influencing respondents' selections rather than capturing their broader GenAI usage patterns.

Internal Validity. As this study relies on cross-sectional survey data, it identifies associations rather than causal effects. A key confounding variable is students' prior technical expertise, as those with programming or data science backgrounds may be more inclined to use GenAI tools, potentially skewing results. Since this factor was not explicitly controlled for, GenAI adoption rates may be overestimated. Additionally, the timing of the survey (winter term 2024/2025) may have influenced participa-

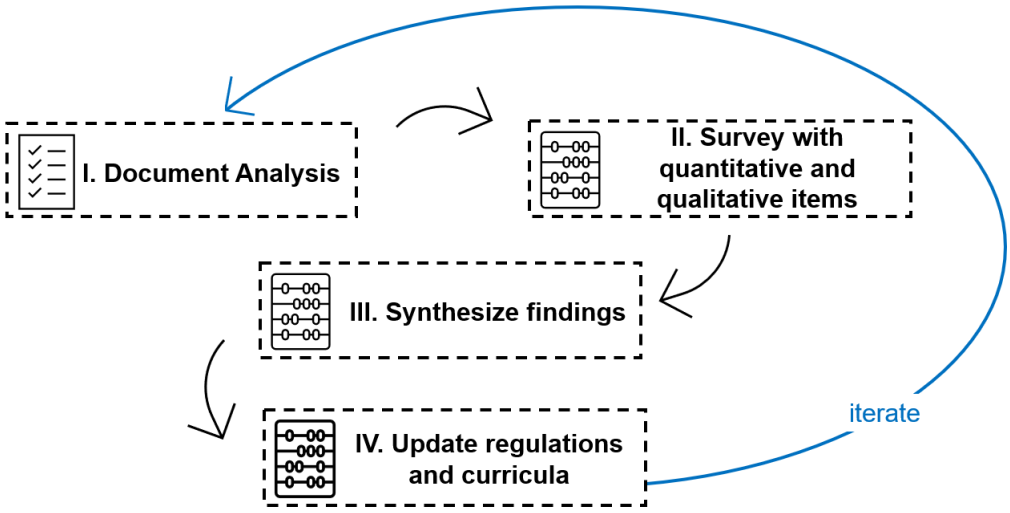

Figure 2: Visualization of the GenAI Adoption Framework.

tion, with later-semester students, particularly those in internships, being underrepresented, leading to selection bias. Furthermore, the study did not distinguish between voluntary GenAI adoption and mandatory use, which is essential for understanding students' true motivations but was not accounted for.

External Validity. The study's restriction to the case context limits its generalizability, as GenAI policies and educational cultures may differ across institutions. Language barriers may have led to the underrepresentation of international students, reducing the diversity of perspectives. Additionally, disparities in digital literacy and financial resources were not considered, meaning students with limited access to premium GenAI tools may engage with them differently, potentially skewing the findings.

Conclusion Validity. The survey study relied on descriptive statistics from Likert-scale responses, limiting the ability to establish statistical significance or detect subtle GenAI usage patterns. Open-ended responses were analyzed qualitatively, but subjective categorization may have introduced bias, potentially overlooking nuances. Additionally, survey dropout rates could have skewed results, as students more engaged with GenAI or willing to complete surveys may be overrepresented. Without data on dropout reasons, the impact on findings remains unclear.

7 CONCLUSION AND FUTURE WORK

Our study investigated the adoption of GenAI tools among students in information systems disciplines at a German university of applied sciences, addressing how students utilize these tools and how institutions can systematically integrate GenAI into their curricula and regulations.

The key contribution of our paper is the GenAI Adoption Framework for Higher Education. To facilitate structured GenAI integration, we developed an iterative approach consisting of four steps: *1) Document Analysis, 2) Quantitative and Qualitative Surveys, 3) Synthesis of Findings, and 4) Updating regulations and curricula*. Our framework assists institutions in proactively adapting, promoting responsible AI usage, and preserving academic integrity as technology rapidly evolves.

Furthermore, our findings indicate that a significant majority of students actively engage with GenAI tools in their academic work: 85.43% of surveyed students use AI-powered applications, with ChatGPT being the most frequently mentioned tool. The primary use cases include research (40.15%), programming (37.8%), and explanations or learning support (34.65%). However, despite widespread adoption, there remains substantial uncertainty regarding institutional policies governing the use of GenAI. Over 71% of students were unsure whether their AI usage aligns with university guidelines. This suggests a communication gap between regulatory bodies and students.

Our future research will go in two directions.

First, we want to further evaluate our AI adoption framework. To do this, we want to conduct more case studies at other institutions and gain more experience with the framework in order to improve it. Secondly, we want to iteratively improve the guidelines and curricula at our own university to keep pace with the rapid developments in the field of GenAI. Furthermore, future research should examine how reliance on GenAI impacts students' cognitive skills, including critical thinking, problem-solving, and creativity.

In particular, our case study suggests that many students lack awareness of GenAI regulations, but the reasons behind this gap are unclear. Further studies should investigate why students are uninformed about policies—whether this is due to ineffective communication, lack of interest, or ambiguity in guidelines. Finally, research should explore how GenAI tools might evolve to better serve educational contexts. As GenAI technology advances, institutions must continuously adapt their teaching strategies and assessment methods to reflect the evolving capabilities of these tools.

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