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AI in Academic Contexts: Understanding Students' Perception of Its Role, Benefits, and Risks

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TABLE OF CONTENTS

Abstract

This study investigates the role and the perception that university students have of Artificial Intelligence (AI) tools within their academic paths, with the specific aim to analyze the Italian and French contexts. For this purpose, the research implements a mixed methodology approach, by combining the use of a survey and a set of interviews. Both of the methods were directed to a population composed by students of French and Italian universities, independently from their age, field or level of study. 170 students participated in the online survey, while interviews were conducted with a total of 16 participants. The obtained results showed how students are in general familiar with AI tools, frequently using them as study aids. Among the tools mentioned by the participants, ChatGPT emerges as the most favorite, along with other Large Language Models. The specific roles covered by these instruments were found to vary from person to person, yet the most common applications comprehend research assistance, text comprehension, summaries, and exams preparation. While most of the students were satisfied with the use of AI for university, concerns were raised, especially regarding the reliability of the results and the fear of over dependence. Moreover, factors like gender and nationality were found to influence the students' attitude towards AI, while attitude, frequency of use and the presence of concerns were discovered to have an impact on the satisfaction level. Lastly, participants strongly emphasized the need for proper instruction on the use, risks and benefits of AI tools, as well as regulatory improvements regarding their utilization in educational contexts.

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1. Introduction

This study is situated within the field of recent-contemporary literature regarding the new, controversial topic of Artificial Intelligence (AI). The research focuses on the analysis of a particular aspect of AI, concerning its applications in academic contexts, exploring the role that AI tools cover for university students on an international level and investigating the related perceived benefits and risks.

1.1 Context of the Research

This research occurs within the context of a fast changing world environment, characterized by quick-paced evolutions on many levels simultaneously: politics, the natural environment, economics and society are indeed found to be in a constant metamorphosis, that requires individuals to become more dynamic and adaptable to changes day after day.

Within this scenario, a pivotal role has been covered by the progressions in the technological field, which strongly affect people's daily environments from various perspectives.

A major impact in these terms was given by the development of Artificial Intelligence, a highly dynamic area of technology which has seen its capacities improve exponentially over the last few decades, reaching a potential that has not been completely acknowledged yet. As mentioned by Cisek in one of his publications on the topic, "...it is quite obvious that AI will dramatically change all areas of life in the near future" (Cisek, 2021, preface).

With a technology that mostly leverages pattern recognition capabilities, Artificial Intelligence is part of the broader context of Digitalization, the Internet of Things and the 4.0 Industry era (Vieweg, 2021), and it has already entered many of our everyday realities, thanks to intelligent systems able to solve real-life problems in every area where they are needed, from engineering to finance, medicine, cyberspace, human-machine interactions and more (Fujita *et al.*, 2020).

Of equally high importance is the role played by AI within the educational field, where intelligent machines provide a vast range of solutions for administration, instruction and learning (Chen *et al.*, 2020) and new applications are still being introduced.

However, ethical concerns have arisen, related to the massive changes brought by AI to people's everyday lives, both personally and professionally. Questions and issues have unfolded across many diverse aspects of AI, especially in terms of success, trust, reliability, errors and limitations (Vieweg, 2021).

Such a framework necessarily requires a proactive and informed approach from individuals: it is indeed imperative to find best practices to profit from AI without being overwhelmed by it, carefully considering the benefits and risks that may arise from substituting human activities with automatized ones.

Existing literature has demonstrated how individuals naturally develop opinions and concerns with regard to the presence of AI inside their professional and personal lives. For instance ,humans are likely to feel peculiar emotions when receiving outputs from intelligent machines, sometimes instinctively perceiving them as having a mind (Shank *et al*., 2019) and anthropomorphizing them to the point where, when interfacing with AI, they naturally feel reliability and trust (Ryan, 2020).

People's perception of Artificial Intelligence encompasses a greater spectrum of opinions, beliefs and emotions which has not been fully studied yet, and that inherently affects their interaction with intelligent machines.

1.2 Aim of the Research

Human interactions with intelligent machines are one of the fulcrums of the studies on AI. Applications within the educational field, in particular, represent a fundamental point in preparing future generations to a more technological future and fostering innovation in academic contexts, as well as the development of brand new abilities and competencies needed in the world of employment of tomorrow.

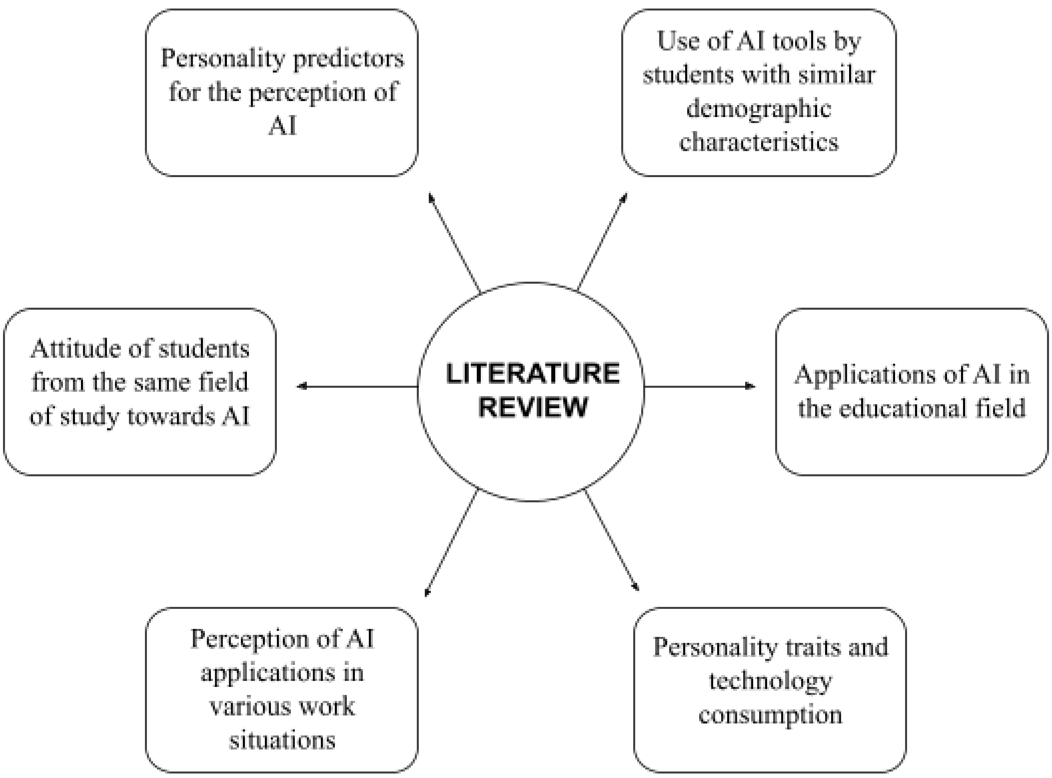
In light of this, the study aims to focus on the role that AI plays for university students and the opinion that scholars have of it. The research also aims to make a comprehensive analysis of the factors influencing the perception and, moreover, to study the possible presence of differences between diverse groups of scholars based on their demographics, personality and field of study.

1.3 Gaps in the Literature and Problem Statement

Extensive research was conducted, with the aim of reviewing the prior studies regarding the relationship that involves students and Artificial Intelligence, and the general perception of AI by individuals.

The current body of knowledge already thoroughly tackles multiple aspects of these topics, with research mostly focusing on identifying common personality traits influencing the perception of technology (Park & Woo, 2022; Hamburger & Ben-Artzi, 2000), as well as capturing individuals' feedback on the application of intelligent machines in different work situations (Abdullah & Fakieh, 2020; Henkel *et al.*, 2020; Vieweg, 2021; Gado *et al.*, 2022). On the other hand, for what concerns AI in the educational field, existing literature has mainly studied its applications, both present and potential (Chen *et al.*, 2020; Ahmad *et al.*, 2021), the potential benefits of AI usage for international students (Wang *et al.*, 2023b) and the perception and use of AI by specific groups of students, mostly within the same university or field of study or having very similar demographic characteristics (Chan & Zhou, 2023; Von Garrel & Mayer, 2023; Țală *et al.*, 2024). Published works have thoroughly analyzed the perception of AI among medical field students, as well (Doumat *et al.*, 2022; Kimmerle *et al.*, 2023; Li & Qin, 2023). The main topics investigated in existing literature have been summarized in Figure 1.

Figure 1. *Existing literature close to the topic of this study*



Source: Author's work

In light of such analysis on pre-existing research, a gap within the literature was identified. Specifically, a lack of study has been found with regard to the role assigned to AI and the perception of it among students of different demographics, personality traits and fields of study within their academic journey. Moreover, research on these topics, with a focus on the Italian and French contexts, was found to be scarce.

Given these considerations, this study's aim was condensed into two pivotal research questions:

1. *What is the role students give to AI within their academic journey?*
2. *What influences their perception of the tool?*

With these premises clarified, it is possible to assert that this study integrates into the existing literature as a more comprehensive, cross-sectional piece of research. Building on previous analyses, indeed, it gains new insights by:

- ➔ running an analysis on a sample that is varied and different with respect to the already analyzed ones, and allows comparisons between different universities' students. For this purpose, Italian and French universities' scholars were chosen as the target audience
- ➔ studying the effect of field of study, nationality, personality and residence on the students' perception of AI, these being among the less studied variables in the existing literature
- ➔ exploring the students' use of AI for university purposes and the presence of potential concerns
- ➔ testing whether the frequency of use of the tools and potential concerns about them have an influence on the students' perception of AI

These goals allow the study to contribute to the existing literature and enhance the overall knowledge on the topic by offering new, valuable insights.

1.4 Methodological Approach

The aim of the research, together with the approaches implemented in the previous literature on similar topics, naturally directed this study towards a mixed methodology, integrating both a quantitative and a qualitative approach.

The study, in particular, was executed through a survey and qualitative interviews, synergistically integrated to address the two research questions.

The sample was chosen among scholars of Italian and French universities, with the aim of allowing the comparison of different demographics, as well as diverse cultural and educational backgrounds. For both the survey and the interviews, a convenience sampling method (Chan & Zhou, 2023) was adopted to select the specific participants.

The questionnaire was administered using the Qualtrics platform for online surveys, while results were analyzed with SPSS, testing the potential presence of relationships among the studied variables.

Excel was instead used for the qualitative examination of the interviews' outcomes.

2. Literature Review

2.1 What is Artificial Intelligence?

The expression *Artificial Intelligence* (AI) refers to a broad set of concepts, related to the ability of computers or other machines to recreate human, intelligent behavior. AI can also directly indicate software and programs able to perform tasks that normally require human intelligence (Oxford University Press, 2023).

Existing literature defines AI in many different ways, but generally the concept encompasses a set of innovative machines endowed with a certain level of intelligence and capable of executing tasks that are normally reserved for humans, such as cognitive processing, decision making, learning and adapting to the environment (Chen *et al.*, 2020). The continuously increasing presence of AI within people's everyday lives and conversations is linked to the greater maturity that technological developments have reached for its implementation in different fields. Specifically, improvements in algorithms, the availability of massive data, increasing computational power and storage at low cost were key drivers of AI's spread in recent years (Ergen, 2019). What differentiates AI from previous technological instruments is the *intelligence* factor itself: machines, in this sense, are in fact able to mimic the human brain's ability to establish inferences among concepts and ideas, consequently being capable of solving problems and interacting with the user (Ergen, 2019). Moreover, in the case of Generative AI, the tools leverage their intelligence to learn from experience, and adapt on the basis of the new informational inputs they receive (Țală *et al.*, 2024).

Such great capabilities, anyway, necessarily need the insertion of a pattern by humans. Artificial Intelligence algorithms are, in fact, strongly dependent on human-generated data, as well as data gathered through human-created systems. This aspect has to be thoroughly considered when discussing AI's potential: since their intelligence is derived from human guidelines, the presence of biases in those guidelines will also transmit into the machines' outputs (Ntoutsi *et al.*, 2020).

2.2 History of Artificial Intelligence

Investments on Artificial Intelligence, as we see it today, began in the 20th century. Already in the 1950s, the *Imitation Game* (also called the Turing Test) was introduced to assess the intelligence of a machine, based on the capability of humans to recognize the difference between the device and another human. If this same difference was not identifiable, then the machine was considered intelligent (Ergen, 2019).

A few years later, in 1956, the term Artificial Intelligence was officially coined during the Dartmouth Conference: a major event for the future of AI, since substantial groundwork for forthcoming research on this topic was laid.

During the time period between the 1960s and the 1990s, many AI related inventions were implemented, like ELIZA, the first Natural Language Processing chatbot (Ciesla, 2024), and a precursor of Deep Learning in 1965 (Ergen, 2019). These innovative technologies strongly changed individuals' approach to technology and started spreading vastly in the 2010s, when AI products underwent a "mass-adoption" (Ergen, 2019, p.2).

Nowadays, most of the applications developed with Intelligent Machines exist under the name of Machine Learning, an expression that refers to the use of statistical methods with the aim of finding patterns and relationships among large amounts of data. A widely used method of implementation for AI also consists of Deep Learning, where Machine Learning mechanisms are designed to reproduce the network of neurons inside the brain, providing a more capillary distribution of inputs and higher accuracy of results but, at the same time, requiring a greater amount of data to function (Ergen, 2019; Bishop & Bishop, 2024).

A great interest has been generated by the recent introduction of Large Language Models (LLMs). These AI based models are, among their various capacities, able to recognize and generate text, and now constitute the skeleton of many famous chatbots, such as ChatGPT (Chan & Zhou, 2023).

2.3 Areas of Application of Artificial Intelligence

Since its first implementations, investments and consequent innovations in Artificial Intelligence have flourished. Nowadays, the applications of AI range widely across multiple fields, with 75% of global knowledge workers reportedly using it for their jobs (Microsoft, 2024).

Among the various uses that individuals do of Artificial Intelligence, these applications have strongly paved their way in the educational field. The intelligent machines have proven to be helpful assistants to teachers and students, providing support through many diverse tools, like intelligent tutoring systems (Chen *et al.*, 2020) and chatbots (Balabdaoui *et al.*, 2024).

AI is also expanding its role within the medical field, potentially leading to a revolution in patients' healthcare in the upcoming years, with a level of accuracy that could surpass that of human specialists (Ahmad *et al.*, 2021; Doumat *et al.*, 2022; Ferrara, 2023; Zendaoui *et al.*, 2024).

Yet, the application of AI tools has received positive feedback in many other sectors, as well: in the finance industry, for instance (Aleksandrova et al., 2023), Artificial Intelligence has facilitated contracting and risk-sharing thanks to its data analytics capacities, which have already overcome many difficulties related to empirical finance research (Cao et al., 2024).

Machine Learning's implementations have also innovated the retail sector (Cao, 2021; He & Zhang, 2023; Srivastava & Pal, 2024), and mention should also be made of the important innovations that Artificial Intelligence has brought to the automotive industry, contributing to the profound changes affecting the sector worldwide, and "designing the mobility of the future" (Schlicht, 2023).

The existing and potential uses of AI in businesses are even more numerous than those presented in this overview, which only provides an insight into its most common applications.

2.4 Contradictions and Ethical Issues

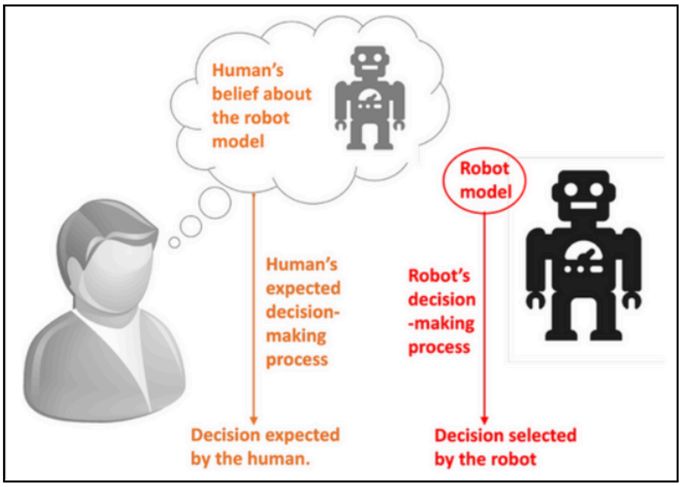
Such an increasingly strong presence of Artificial Intelligence tools within people's everyday lives does not come without concerns. Existing studies on the impact of AI in different areas, indeed, have highlighted the presence of ethical issues and contradictions related to intelligent machines, emphasizing the importance of an informed and responsible use and the necessity for proper regulatory frameworks.

As previously mentioned, intelligent machines' algorithms work by replicating patterns and inputs that they receive externally. The potential presence of biases, in the data that AI acquires, naturally leads to biased outcomes: hence, algorithms may reproduce or amplify unequal and discriminatory patterns in terms of gender, race or other groups (Ntoutsi et al., 2020; Hall & Ellis, 2023; Harrer, 2023). Additionally, in the case of Large Language Models, research has shown how their answers were sometimes found to sound correct, but actually be wrong (Teubner *et al.*, 2023).

Moreover, the structure of AI tools naturally leads them to perform better the more private data they have of their users (Willems *et al.*, 2023). Yet, the frequent unawareness that individuals have about the data they share can lead to privacy issues: for instance, simply through passive registrations done with a webcam, AI can manage to assess people's important private information such as their health conditions and psychological status. In other cases, analyses done on an individual's internet searches can lead to insights regarding their ideas, opinions or political alignment (Wagner *et al.*, 2020).

The interaction that establishes between individuals and AI represents another contemporary topic of discussion. This relationship can indeed generate misalignments between the human's expected outcome for a certain input, and the actual result of the intelligent machine (See Figure 2). This is mostly due to incorrect human expectations, that assume AI capable of producing outputs which are non-compatible with the machine's real possibilities (Sreedharan, 2023).

Figure 2. *Diagrammatic representation of a common misalignment*



Source: Sreedharan, 2023

Moreover, existing literature reports how individuals' behaviors when interfacing AI are occasionally influenced by biases, such as automation biases and selective adherence (Alon-Barkat & Busuioc, 2023).

Finally, a study conducted by Frey and Osborne (2017), on the job risk level related to computerization in the US, provided worrying insights on job displacement. Almost half of the jobs in the US, indeed, were found to be at a high risk of being automated by the next 20 years. Moreover, computerization was predicted to mostly affect jobs that require low skills and provide low wages, suggesting the future need for these workers to reallocate themselves (Frey & Osborne, 2017). Microsoft recently reported how 53% of the global knowledge workers are afraid to admit using AI for the most important tasks of their jobs, because of the fear of looking replaceable (Microsoft, 2024).

3. Framework around the literature gap

To establish a proper methodology, studies on the factors influencing the perception of Artificial Intelligence, and its role in academic contexts, were consulted. Their findings were later used as starting points for the construction of the survey and the interviews' questions.

3.1 The role of Artificial Intelligence within Academic Contexts

Artificial Intelligence has brought impactful changes in the educational field, altering the habits and methods adopted by both professors and students and introducing new, smart ways to teach and study.

3.1.1 Areas of application

The applications of AI in the educational field range widely, comprehending administrative functions, teaching and the learning context (Chen *et al.*, 2020). In the academic branch, specifically, AI has become pivotal: universities underwent an evolution in many countries and overcame their role of conveying traditional heritage and instruction, by introducing technological innovation and becoming points of reference for new teaching and learning methods (Jafari & Keykha, 2023).

- *AI for instruction and administration*
  Within the administrative context, AI paved its way by the means of innovative computer technologies and intelligent web-based systems, such as Grammarly, Ecree, PaperRater, and Turnitin. These platforms managed to improve the automation of common tasks like exam grading, student tasks' review and real time feedback creation (Chen *et al.*, 2020; Chan & Hu, 2023). Another notable application regards the reception of evaluations: AI has indeed simplified the creation and delivery of students' comments and feedback on teachers' performances (Salas-Pilco & Yang, 2022). Furthermore, AI tools can provide predictive analyses of student performance and progress (Salas-Pilco & Yang, 2022; Wang *et al.*, 2023a), as well as customized content creation for every subject and intelligent personalization tools, like DeepTutor and AutoTutor, based on the learning method of the individual student (Chen *et al.*, 2020).

Virtual reality has also changed the engagement in lessons for both teachers and students, by creating a practical learning experience. Such innovation particularly impacted medical education, with students being able to see operations and study human anatomy based on realistic images (Chen *et al.*, 2020; Kong *et al.*, 2021).

AI is also leveraged for the enhancement of academic integrity, both to check plagiarism in students' works and to ensure an online supervision of their activities on digital devices (Chen *et al.*, 2020).

- *AI in learning*

  Recent and contemporary studies highlighted how students' use of AI widely ranges, encompassing different tasks and roles.

  Many scholars were found to see AI tools as efficient buddies, helping them in various activities, from brainstorming to exam preparation and proofreading (Balabdaoui *et al.*, 2024).

  AI also tracks learning progress and facilitates collaborative learning through web-based platforms. Students can use AI to create personalized learning experiences, tailored to their needs and capabilities (Chen *et al.*, 2020).

  The use of chatbots has been a pivotal innovation for scholars as well (Salas-Pilco & Yang, 2022; Stepanenko & Stupak, 2023). LLMs like ChatGPT and Google Bard, for instance, are being employed as general-purpose tools, assisting with tasks such as mathematical operations development, interviews transcription, grammar checking, translations, programming tasks, qualitative data analysis, literature reviews and paraphrasing (Balabdaoui *et al.*, 2024) as well as researching, brainstorming, summarizing and writing composition (Chan & Hu, 2023).

  In this context, existing literature also highlights the important role played by chatbots in helping non-native speakers, by offering them writing assistance and text review (Chan & Hu, 2023).

3.1.2 Benefits

The introduction of AI tools in the educational field reportedly brought significant benefits and advantages for students and educators. Specifically, the leveraging of intelligent machines has enhanced efficiency in administrative and teaching contexts, improving the effectiveness of learning experiences, reducing time expenditures for professors, ensuring consistency in scoring (Chan & Hu, 2023) as well as fostering their evidence-based decision making (Wang *et al.*, 2023a). The development of AI has also granted professors the possibility to develop better, more personalized and specific pedagogical tools for their students, resulting in an improved experience for both parties. Furthermore, the introduction of tools to enhance the academic integrity of students has reportedly brought benefits to instructional quality (Chen *et al.*, 2020).

A difference is also highlighted, in existing literature, between AI and Computer Based Training (CBT): AI is reportedly more effective due to its high personalization level, whereas the generalized approach of CBT may not address the real needs of every individual student (Chen *et al.*, 2020).

Moreover, students have demonstrated to benefit from AI implementations, with positive results in terms of improved grades, a better retention of information and a stronger set of skills to apply to real-word scenarios. Such results have been extensively studied in recent literature, with findings showing how the use of AI generally fostered students' motivation and personal capabilities in terms of information retention (Chen *et al.*, 2020; Chan & Hu, 2023). AI tools are also pivotal for academic research, leveraging their capabilities to analyze large volumes of data (Güner *et al.*, 2024).

3.1.3 Biases and risks

AI implementations within the academic context have brought challenges as well. Specifically, with regard to Generative AI, limitations have been found in terms of ethics, plagiarism and academic integrity (Chan & Hu, 2023) and in relation to the reliability of the outputs. For instance, ChatGPT was sometimes discovered to generate answers that sounded plausible and true, but were indeed erroneous (Von Garrel & Mayer, 2023). Moreover, analyses were conducted to study the quality of the responses to academic writing prompts, finding that the produced text outputs were often original and appropriate to the topic, but also contained inappropriate literature references (Chan & Hu, 2023).

Another important limitation regards the presence of biases: as in other fields of application, AI tools have been found to produce biased, inaccurate or harmful answers when trained with biased datasets (Harrer, 2023). Additionally, concerns have been raised about the privacy and security of AI, especially for the risks of data breaches and data misuse, since a large amount of information is required to use these tools (Güner *et al.*, 2024).

More generally, the use of AI tools within the academic context has raised issues in terms of integrity, due to the difficulty of determining whether a piece of work was created by a human or a machine, and consequently questioning the boundaries of ethical behaviors in academic writing, especially concerning plagiarism, copyrights and authorship, particularly because students have sometimes been found trying presenting AI-generated works as their own (Chan, 2023; Cotton, Cotton & Shipway, 2024). Further concerns are also present, related to the potential loss for students of holistic competency development, following an increasing use of AI tools, especially in terms of creativity, originality and critical thinking, which intertwine with the promotion of academic dishonesty, leveraging *AI-giarism* (Chan, 2023; Chan & Hu, 2023).

Finally, studies have also analyzed how some professors were found to be not adequately prepared for the AI introduction into their teaching system, eventually causing dissatisfaction with its adoption. Potentially, those who feel unprepared to implement AI may feel threatened and be concerned about a possible disruption to their work (Wang *et al.*, 2023).

3.1.4 Academic regulations

The implementation of Artificial Intelligence within academic contexts has necessitated universities to update their regulations. Despite the tools generally being useful for studying and learning, concerns have arisen due to the potential possibility for students to falsify their academic performances. Recent studies have found how, sometimes, scholars use AI tools for exams plagiarism, presenting AI works as their own to improve their proficiency (Jafari & Keykha, 2023; King, 2023; Cotton, Cotton & Shipway, 2024). This consequently reduces their competency development and critical thinking, and raises ethical issues about the use of AI for academic purposes (Chan, 2023; Chan & Hu, 2023).

Some have responded to these issues by advocating a total ban of AI tools from schools and universities (Volante *et al.*, 2023). Many universities are now implementing detection tools to identify work created by chatbots, particularly ChatGPT. However, such instruments were sometimes found to produce false positives, or failed to correctly identify essays generated with AI. Moreover, existing studies report the possibility for students to evade detection by adjusting the AI generated text. In light of this, many schools in the USA took the decision to ban the use of ChatGPT for academic purposes (Volante *et al.*, 2023).

The European Commission has developed a Digital Education Action Plan, aimed at better managing the relation between teaching, learning and AI through ethical guidelines for

European schools and universities. These directives were formulated taking into account the groundwork laid with the General Data Protection Regulation and the Artificial Intelligence Act, and were designed to allow a safe and ethical use of these technologies inside the educational contexts (European Commission, 2022). The Digital Education Action Plan highlights how Machine Learning tools in schools and universities require a variety of data to function, ranging from educational achievements to students' demographics, together with a series of micro-level data obtained by the interaction with the digital devices, making it imperative to ensure data and privacy protection. More broadly, the guidelines aim to address the issues and concerns that arose with the implementation of AI in education, and focus their improvement plan onto two aspects: the growth of a digital instruction ecosystem and the development of digital skills, for a digital transformation of education (European Commission, 2022).

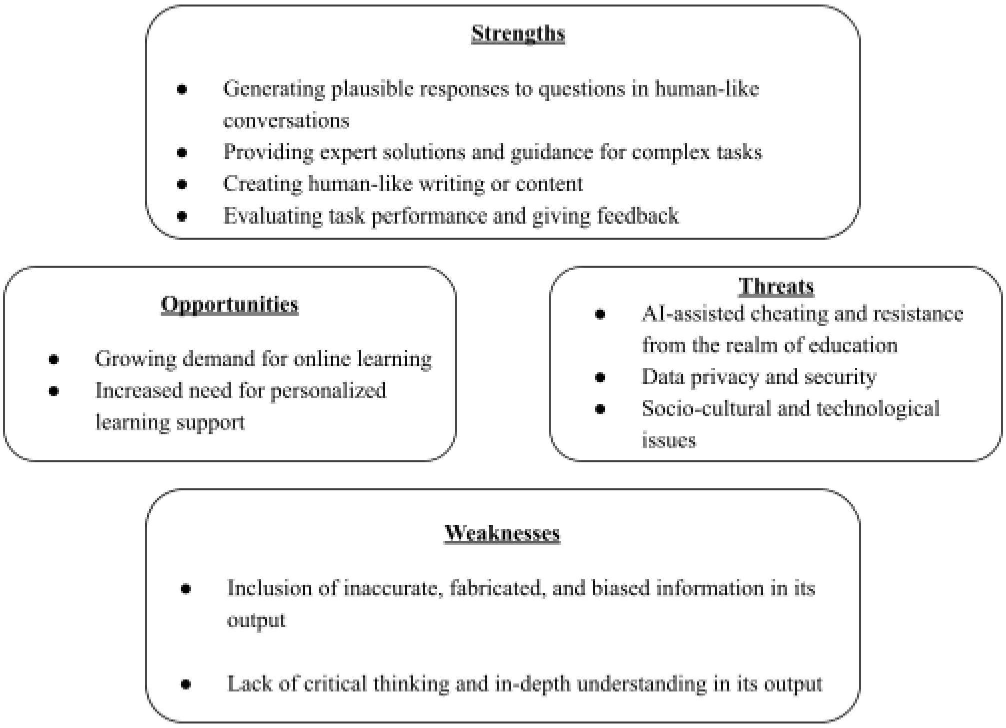
Italian universities have chosen not to implement a complete ban on AI, as instead happened in many US institutes, yet different perspectives have arised: on one side, professors have demonstrated a positive attitude towards the implementation of AI tools within their courses, to improve students' learning experience; on the other hand, concerns have been expressed regarding the difficulty to ensure fairness and detect plagiarism (Castigli, 2023).

3.1.5 SWOT analysis

Figure 3 presents a SWOT analysis from the study of Zhu *et al.* (2023), highlighting the strengths, weaknesses, threats and opportunities of the tool ChatGPT within the educational context. As previously mentioned, Large Language Models like ChatGPT have sometimes been found to generate plausible, yet erroneous answers to given inputs (Von Garrel & Mayer, 2023), and to be prone to errors due to biases (Harrer, 2023). Zhu *et al.* (2023) discuss how ChatGPT lacks critical thinking and self-awareness, often proposing wrong outputs with a certain level of confidence. However, the well-known chatbot distinguishes itself for the multiple activities it provides for users, from task evaluation to the creation of written contents and the ability to engage in a human-like conversation.

It is also important to consider the context in which AI tools' use is growing: a fast-changing educational environment, characterized by an increasing propension to online learning and personalized learning experiences, certainly encourages the utilization of Artificial Intelligence for instruction. On the other hand, the development of such tools is threatened by their internal contradictions (as already discussed in sub-paragraph 3.1.3), and a certain level of opposition from the educational sphere, due to the potential challenges associated with their use (Zhu et al., 2023).

Figure 3. *SWOT analysis of ChatGPT in education*



Source: Based on Zhu *et al.*, 2023

3.2 University Students' Perception and Concerns about AI

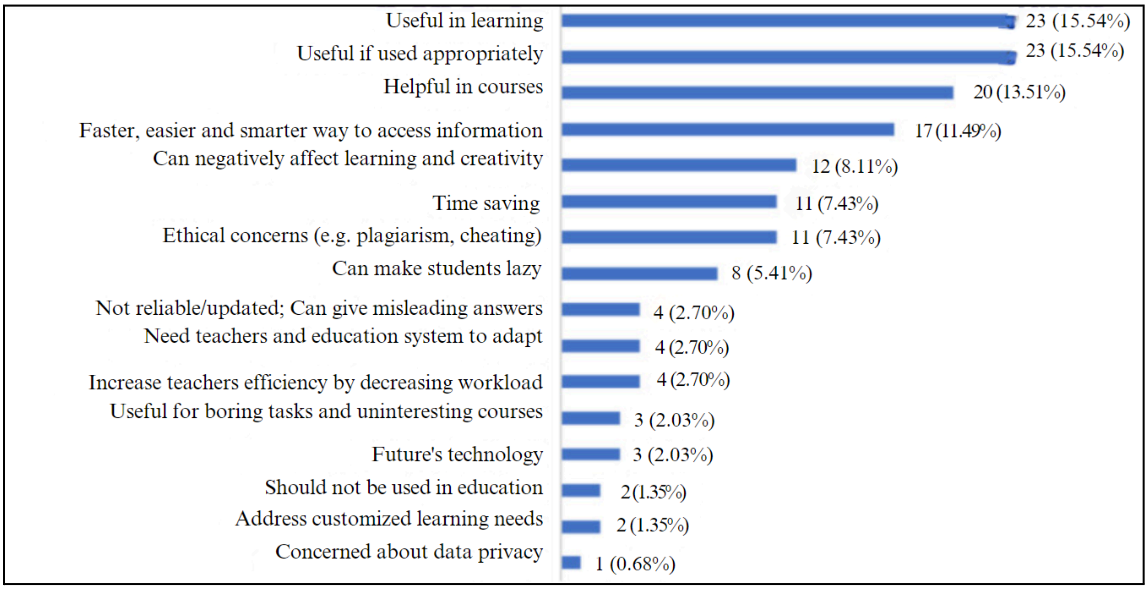
Existing literature presents a wide variety of research on students' perception of AI.

In terms of the level of information, students were generally found to have a proper understanding of AI, but do not consider themselves as experts (Idroes *et al.*, 2023).

In some cases, relations were found between the field of study and the familiarity with AI tools, with students from scientific majors demonstrating a more positive attitude towards AI compared to other fields (Balabdaoui *et al.*, 2024). Regarding the perceived benefits, many scholars reportedly stated how the introduction of AI tools in academic contexts can be highly beneficial, considering the many smart applications of intelligent machines for university purposes, yet education is needed to train students for their usage (Idroes *et al.*, 2023).

Indeed, the increasing use of Artificial Intelligence tools by many students in their study path does not exclude the presence of concerns and uncertainties. Among the most common aspects of skepticism for scholars, literature emphasizes the existence of hesitations with regard to the reliability, accuracy and trustworthiness of AI tools (Balabdaoui *et al.*, 2024; Güner *et al.*, 2024), as well as reservations for the possible presence of biased outputs (Balabdaoui *et al.*, 2024). Moreover, the existence of ethical concerns is underscored, with regard to an inappropriate use of chatbots for the execution of exams and assignments. Students also reported having concerns about possible negative impacts of AI in terms of creativity and productivity as well as over-dependency, and for the loss of data privacy, as also shown in Figure 4 (Güner *et al.*, 2024).

Figure 4. *Students' opinions about the academic use of ChatGPT, collected in one recent study on the topic*



Source: Based on Güner *et al.*, 2024

3.3 Personality Predictors of Technology's Perception

Studies have been conducted regarding the potential presence of a relationship between individuals' perception of AI and their personality traits.

In terms of the broader context of technology consumption, existing literature investigated the possible interactions between personality and attitude towards technological tools. A fitting research for the aim of this study, in this scenario, is that of Hamburger and Ben-Artzi

(2000). This inquiry was centered on the evaluation of potential relations between the traits of extraversion and neuroticism, and individuals' attitude towards Internet use. The findings indicated a peculiar relationship, positively relating the use of Internet services to extraversion for men, while for women a positive relationship was found with neuroticism (Hamburger & Ben-Artzi, 2000).

Analyses on attitude predictors towards AI were conducted as well. A pivotal study in this context is by Park and Woo (2022), which assessed whether the Big Five personality traits, together with individuals' personal innovativeness, affect the attitude towards AI. Attitude was measured on the basis of three dimensions, these being sociality, functionality and affective components.

The results of this study demonstrate the presence of unique correlations between personality traits and attitude. Specifically, extraversion was found to be related to negative emotions and low functionality, while agreeableness caused mixed emotional responses but was discovered to be positively associated to sociality and functionality. Moreover, conscientiousness was shown to be related to low negative emotions and high functionality, but low sociality, and neuroticism to be connected to negative emotions but high sociality. Openness, instead, was found to be linked only to functionality (Park & Woo, 2022).

3.4 Gender and Age's Effect on AI Perception

The role of gender and age in shaping the perception of technology and AI was revealed to be influential among diverse existing studies on the topic. In Hamburger and Ben-Artzi's case, as mentioned earlier, gender was found to be part of a cross-relationship involving personality traits and attitude towards Internet services (Hamburger & Ben-Artzi, 2000). More recent literature has focused instead on the direct effect of gender on attitude towards AI, finding that females tend to be more skeptical than males (Balabdaoui *et al.*, 2024).

Age was found to be influential on the perception of AI, as well: studies have shown that younger people have a more positive attitude towards new technology acceptance compared to older people (Park & Woo, 2022).

3.5 Cultural Backgrounds' Effect on Technology Readiness

Existing research studied the presence of potential links between individuals' technology attitude and their cultural backgrounds. For instance, Guhr et al. (2003) conducted an extensive exploration with regard to the relationship between technology readiness and cultural differences. The rationale behind this investigation resided in the importance for businesses to tailor their mobile payments methods, based on individual cultural contexts (Guhr *et al.*, 2003). The results of the study did not fully align with expectations: cultural dimensions were found to be influential on technology readiness, yet in some of the analyzed countries more complex factors were deemed impactful on the acceptance of mobile payments.

A decision was made to start from this study to further investigate the role of cultural backgrounds in the perception of technology, also in light of the possibility to enrich the literature with more recent results.

4. Methodology

4.1 Mixed Method Approach Overview

As anticipated, the structure given to the research questions and, more generally, to the aim of the study naturally led to a mixed methodology approach.

The reasoning behind this choice lies in the nature and scope of the research questions.

The decision to adopt a mixed method was also supported by extensive research, which allowed the recognition of the presence of both benefits and challenges in its adoption (Zhou & Wu, 2022; Grant *et al.*, 2023).

Specifically, Grant *et al.*'s study was adopted as a guideline for the evaluation of the application of a mixed methodology in this study's case (see Figure 5).

The cost and time expenditures were not found to be proper obstacles within the context of this research. Regarding the lack of skill set and training (Grant *et al.*, 2023), such an issue was overcome by the means of wide-ranging research and a consequent understanding of the strategies to use to profit from this methodology.

On the other hand, a mixed method approach grants the study of a more holistic view of the topic (Zhou & Wu, 2022), as well as stronger analysis results, by reducing biases and producing richer, more complete outcomes (Grant *et al.*, 2023).

These aspects being considered, the benefits of a mixed methodological approach were found to outweigh its potential challenges in this study's case.

Figure 5. *Prospect on the benefits and risks of the mixed methodology*

Benefits	**Challenges**
• A need to obtain a more holistic view of the research phenomena • Having multiple lenses to provide greater clarity and detail to answer research questions • Better validation and expansion of overall results • Producing research that makes a higher-level contribution to managerial practice • Enabling researchers to answer "maybe" and "how/why" questions • Bringing research participants and key stakeholders more directly into the research itself • Reducing bias	• Lack of skill set and training to undertake mixed method research (conducting, analysing and interpreting) • Research training is separated into the traditional dichotomy of quantitative and qualitative in academic institutions • Lack of awareness off the benefits of conducting mixed method research • Time to conduct mixed method research (publish or perish!) • Cost to conduct mixed method research • Journal paper bias towards singular methods • Supervisory bias towards singular methods

Source: Based on Grant *et al.*, 2023

Consequently, the following structure was chosen for the conduction of the study:

- A survey was created, with the aim of collecting quantitative data to be analyzed with SPSS, and to establish relationships between variables
- Qualitative interviews were scheduled, to be performed after having collected and analyzed the results of the survey. This sequence of methods was chosen in order to answer questions and doubts that may have arisen from the survey analysis, as well as to investigate in a deeper, more specific way the peculiar topics of the research.

Both the methods were used to answer the two research questions, in a synergistic way that integrates the survey and the interviews to enhance the results' completeness.

4.2 Population and Target Audience

The population of the study was chosen to be students of Italian and French universities, in order to extend the scope of the analysis to an international level. Specifically, for Italy, the students who were the subjects of the study were mainly scholars of LUISS Guido Carli and Università degli Studi di Perugia. For French universities the study was limited to the scholars of ISG International Business School. Considering the resources available for the realization of this study, a convenience sampling was implemented (Chan & Zhou, 2023), paired with a snowballing methodology to increase the sample size. Consequently, both for Italy and France, the possibility to receive answers from students of other universities was considered, and those answers were deemed acceptable as well.

4.3 Survey Creation

For the quantitative section of the study, an online survey was designed on the Qualtrics platform, with the purpose of collecting valuable quantitative data regarding students' perception and use of AI within their academic journey.

Existing literature was analyzed by the means of thorough research, to gain specific knowledge on the framework to adopt for the creation of surveys, and to consequently enhance the quality of the tool.

4.3.1 Identification of the research objectives

During this preliminary phase, the objectives of the research were revisited, with the aim of preparing a survey that was aligned with the goals of the study.

As previously mentioned, the following research questions were delineated as the scopes of this study:

1. *What is the role students give to AI within their academic journey?*
2. *What influences their perception of the tool?*

4.3.2 Population recognition and survey accessibility

During this step, the individuals forming the population of the survey were identified.
The target audience for this research was expected to be composed of academic students at any level of university and any course of study, enrolled in Italian and French Universities.
To improve the accessibility of the survey, participants were given the possibility to choose between English, Italian and French as the language for the questions. Considering the target audience, these options made the questionnaire easily approachable for all participants, and helped overcome a common limitation in similar studies on the topic (Von Garrel & Mayer, 2023). Given the presumed characteristics of the chosen population, it was also assumed that the participants had the proper knowledge to answer the survey questions without difficulty.

4.3.3 Sampling plan creation

As anticipated, a decision was made to adopt a convenience methodology for the sampling, to enhance efficiency in terms of time, costs and resources in general.
The online survey created for this study was shared with the target audience through various channels:

- Emails were sent to professors of ISG International Business School in Paris, LUISS Guido Carli and Università degli Studi di Perugia, who were asked to share the survey with their students.
- Participants were also reached directly, through social media channels and emails, extending the distribution coverage to students from other universities as well.

Following the snowballing method, both in the case of Italian and French Universities, students were given the possibility to share the survey link with other scholars, also from different universities, with the aim of enriching the diversity of the sample and obtaining more comprehensive results.
The expected number of responses proved to be difficult to estimate, due to the impossibility of predicting the response rate of the students.

The convenience methodology adopted naturally created a non-probability sample. This characteristic usually leads to a higher presence of biases compared to a probability sample. Moreover, the results of the questionnaire cannot be extended to the whole population (Stratton, 2021). Nevertheless, the analysis' outcomes are representative of the sample units and still allow for the production of useful considerations for the aim of the research.

Furthermore, following the pre-existing literature on similar topics, a choice was made to guarantee anonymity in the survey to reduce the possible effects of social desirability biases (Von Garrel & Mayer, 2023).

A precise time range was defined for the survey results' collection, with the aim of ensuring a final date to start the analysis of the results and avoid additional, new responses after the beginning of the output interpretation. A choice was made to set an expiration date to the survey after two months from the date of its distribution.

4.3.4 Design of the questionnaire

Attention was dedicated to translating the survey objectives into carefully-worded questions, to ensure accessibility and understanding for the sample. All of the questions were crafted in a clear and easily understandable language, and topics were deemed to be coherent with the sample's knowledge and capability to respond confidently.

The structure of the survey complied with the structure that was given to the research, considering the main theme of the study, the survey objectives and the research question.

Figure 6 summarizes the specific framework adopted for the questionnaire, highlighting the main topic of each section and its relevance to the research context.

Figure 6. *Survey framework*

SURVEY SECTION	*TOPIC OF THE QUESTIONS*	*SCOPE WITHIN THE RESEARCH*
Language choice	Choice of the language of the survey	Making the survey more accessible to every sample unit
Introduction	Brief description of the objective of the survey and the research	Engaging the sample units in the research scope

Academic career	Sample units' enrollment in a French or Italian academic course; specific university of enrollment	Limiting the possibility for a non-target individual to answer the survey questions, damaging data quality, and checking the distribution of the survey among universities
Field of study	Field of study of belonging	Collocating each sample unit into their field of study
Demographics	Gender, Age, Nationality, Residence	To be used as independent variables and control variables, and more generally to enrich data specificity
Personality test	Personality tendencies	Identifying the potential belonging of the sample units to *extraversion* and *neuroticism* characteristics; cross-analysis with sample's gender answers
Attitude towards AI	Opinions and attitude towards AI in everyday life	Measuring the sample units' general perception of AI, to be used as dependent variable
AI & University	Use of AI in the academic context	Understanding the role that students give to AI within their university path
Feedbacks	Multiple feedbacks on the academic experience with AI	Grasping the students' level of perceived satisfaction and their potential concerns regarding AI within their academic path

Source: Author's work

Every aspect of the survey was crafted on the basis of specific reasons, directed to the reaching of a strong synergy with the existing literature on the topic and to the answering of the research questions. In particular:

- ***Academic career***

  This section was delineated as a preliminary part of the survey, with the aim of reducing answers coming from non-target individuals. In this section, two questions are indeed posed to the sample units:

  Are you currently pursuing a university path?

  Are you currently enrolled in a course of an Italian or French University?

  A negative answer to at least one of these questions would redirect to the end of the survey, limiting the presence of responses coming from individuals out of the target audience and, consequently, improving data quality. Moreover, in this section, sample units are asked to indicate their University of enrollment, with the aim of better understanding the subdivision of the answers on the basis of the university of belonging.

- ***Field of study***

  Within this section, sample units were asked to indicate the academic field of their university course. Other literature on the topic ran analyses on the different uses of AI from students belonging to different fields of study; anyway existing literature presents a gap on the study of statistical relationships between fields of study and the perception of Artificial Intelligence. In light of this, this parameter was selected as an independent variable for the study, with the aim of testing Hypothesis 1:

  Hypothesis 1: Students' attitude towards Artificial Intelligence tools differs based on their field of study.

  The list of the different fields was created after a comprehensive analysis of Italian and French academic courses, ensuring its preciseness and completeness in order to reduce incorrect or doubtful answers.

- ***Demographics***

  Every demographic variable requested to the sample units covers a specific role for the study's purpose. Specifically:

  1) *Gender and Age*

     As presented in existing research on the perception of AI, gender and age were often found to be related to individuals' opinion on tech innovations. Specifically, younger people tend to better react to new technologies (Park & Woo, 2022) while, from the point of view of the gender, the relationship between the individual and Internet services in general is different for males and females, also depending on their personality traits.

     In particular, the following relations were discovered regarding this aspect: the use of social services on the Internet is positively related to neuroticism in women and extraversion in men, yet the same is negatively related to extraversion in women and neuroticism in men (Hamburger & Ben-Artzi, 2000).

     In Hamburger and Ben-Artzi's research, however, gender analysis is limited to two gender parameters, "male" and "female", and their perception of Internet services. On the other hand, this study extends the analysis also to the non-binary/third gender and considers a more specific dependent variable, the perception of AI.

     In light of these considerations, a decision was made to first analyze the direct effect of just *gender* on the *attitude towards AI*, aiming to see the potential presence of relationships between those variables. Subsequently, it was planned to realize a cross-analysis on *extraversion*, *neuroticism* and *gender*'s effect on the students' attitude, thereby enriching the existing literature on this aspect.

     Finally, given the results already obtained in other studies on the topic (Park & Woo, 2022), *age* was chosen not to be tested again to find relationships.

     The following are the hypotheses related to the above mentioned variables:

     Hypothesis 2: Gender influences students' attitude towards AI

     Hypothesis 3: Gender moderates the relationship between extraversion and students' attitude towards AI

Hypothesis 4: Gender moderates the relationship between neuroticism and students' attitude towards AI

2) *Nationality*

The existing literature investigates the presence of a correlation between cultural backgrounds and technology readiness (Guhr *et al.*, 2003). At the same time, anyway, literature results to be lacking a proper study of the effects of nationality on the perception of Artificial Intelligence. In light of this, a decision was made to first analyze the effect of nationality on the students' *attitude towards AI*, enriching the existing literature on this aspect.

Hypothesis 5: Nationality affects students' attitude towards AI

The survey only presents the three options "*Italy*", "*France*" and "*Other*" as answers for the nationality question. The choice of using a closed question instead of an open one was adopted for a more effective data elaboration: considering that the survey was destined to be shared among students from Italian and French Universities, a major presence of Italian and French sample units was expected. Collecting the answers of other nationalities' units in just one comprehensive group was considered the best choice to adopt, since analyses for each nationality were expected to be poor due to the supposedly low number of individual sample units.

3) *Residence*

This parameter was inserted in the survey to test the potential existence of a correlation between the place where the sample units live and their perception of AI. The existing literature does not present particular findings with this regard; for this reason the results of the study may enrich a section of the literature that is still unexplored.

Hypothesis 6: The place of residence affects students' attitude towards AI

- *Personality Traits Test*

  This represents a pivotal section for the questionnaire, aimed at gaining data to explore the potential correlation among gender, personality and perception of AI. The decision to run such an analysis was supported by the results of existing literature on similar topics, which showed the presence of relationships between gender, personality and internet services use (Hamburger & Ben-Artzi, 2000).

A choice was made not to analyze *extraversion* and *neuroticism* with the same approach of Hamburger and Ben-Artzi, in order not to over complicate the survey, excessively reducing the attention span of the sample as well as the individuals' willingness to complete it, and negatively impacting data quality. This aspect being considered, only six questions per trait were chosen and inserted in the subsequent section of the survey, following the study of Eysenck (1958) on the reliability of a shorter version of the same test used in Hamburger and Ben-Artzi's research. This shorter scale has already been used in various studies that proved its validity (Alexopoulos & Kalaitzidis, 2004), thus it was considered a good fit for this research. An attention check item was also crafted, following the insights offered by existing literature (Gummer *et al.*, 2021), and inserted in the scale to improve data quality, reducing some of the common biases that may arise in survey compiling, like the acquiescence bias (Kam & Meyer, 2015).

- *Attitude Towards AI*

  In this section, the survey aims to collect precious information regarding the sample units' perception of AI within their everyday life. Existing literature was consulted, with the scope of acknowledging the scales used in similar researches to measure this variable. After an extensive review of these studies, a choice was made to adopt the GAAIS by Schepman and Rodway (2023).

  The *attitude* measured with this scale was used as the main dependent variable for this study. This scale was already crafted with an attention check item, which was kept in the survey to enhance data quality.

- *AI & University*

  In this part of the questionnaire, sample units were asked to describe their relationship with Artificial Intelligence in the academic context.

  The introductive question of this section (*Have you ever used Artificial Intelligence tools during your academic journey?*) serves as a dichotomy of the sample, dividing the responding units into two groups, respectively composed of those individuals that never used AI in their academic path and those who did.

In case of a negative answer, the sample was redirected to an open question, asking to explain the reasons behind the decision of not using AI, and was later sent to the *Feedbacks* section. Here, the units were asked to indicate potential concerns by choosing from a list. This set of data was considered useful for a broader understanding of the perception of AI.

Subsequently, this sample group was conveyed to the end of the survey, to avoid improper answers and ensure data quality.

The other part of the units was indeed proposed a set of questions regarding their frequency of use, the tools used and the areas in which they applied AI for academic purposes.

Frequency of use was examined to check the potential existence of a relationship with students' satisfaction level with regard to AI tools in their academic journey.

Other questions' scope was to collect data regarding the use that students do of AI within their academic path, for a more qualitative analysis. The queries for this section were carefully selected based on recent literature on pertinent topics (Von Garrel & Mayer, 2023; Idroes *et al.*, 2023).

- *Feedbacks*

  This section was aimed to collect precious information, regarding students' opinions and perceptions towards AI in their academic journey. The main variable measured here was the *level of satisfaction* with AI.

  These hypotheses were to be tested with the information gained in this and the previous sections:

  Hypothesis 7: Students who use AI tools more often within their academic journey are more satisfied of AI than those who use them more rarely

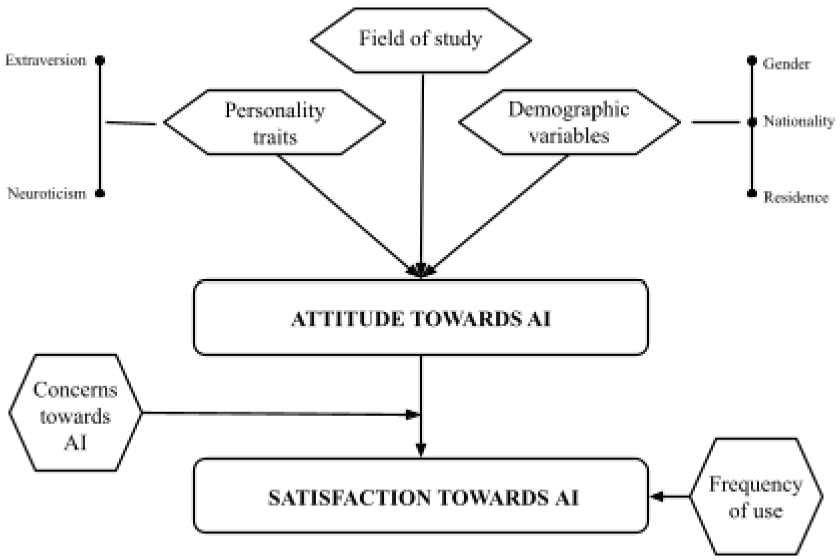
  Hypothesis 8: A positive attitude towards AI is associated with higher levels of satisfaction towards AI tools.

  Within this part of the questionnaire, a question regarding the *concerns* on the use of AI was inserted, dually beneficial for the purposes of the study: on one hand, it allows to collect precious data regarding the possible presence of issues related to students' use of Artificial Intelligence tools for university. Moreover, the presence of *concerns* was planned to be used as a moderation variable for the relationship between *positive attitude* and *satisfaction*, testing the following hypothesis:

*Hypothesis 9***:** Concerns about AI use (e.g., ethical concerns, privacy issues) affect the relationship between positive attitude and satisfaction of AI in academic contexts

The whole set of questions in the survey was deemed to be designed in an effective and functional manner, after a peculiar analysis of pieces of related literature (Charbonneau, 2007). Comprehensively, the survey aimed at analyzing a complex framework of relationships between the variables in the survey, by testing a set of specific hypotheses (see Figure 7 and Figure 8).

Figure 7. *Framework of the variables' analyzed relationships in the survey*



Source: Author's work

Figure 8. *Hypotheses to be tested through the analysis of the survey results*

	Hypotheses to be tested
HP 1	Students' attitude towards AI tools differ based on their field of study
HP 2	Gender influences students' attitude towards AI
HP 3	Gender moderates the relationship between extraversion and students' attitude towards AI
HP 4	Gender moderates the relationship between neuroticism and students' attitude towards AI
HP 5	Nationality affects students' attitude towards AI
HP 6	The place of residence affects students' attitude towards AI
HP 7	Students who use AI tools more often within their academic journey are more satisfied of AI than those who use them more rarely
HP 8	A positive attitude towards AI is associated with higher levels of satisfaction towards AI tools
HP 9	Concerns about AI use (e.g. ethical concerns, privacy issues) affect the relationship between positive attitude and satisfaction of AI in academic contexts

Source: Author's work

4.3.5 Pilot test questionnaire and survey distribution

A decision was made to conduct a pilot test questionnaire, to identify the presence of potential bugs and improve the overall efficacy of the tool.

The pilot test provided important insights on formal and technical changes that needed to be conducted to improve the questionnaire's accessibility. No structural modifications were deemed necessary.

Subsequently, the survey was distributed to the target population as anticipated in subparagraph 4.3.3.

4.4 Steps for the Analysis of Survey Results

The book *Applied Regression Analysis and Other Multivariable Methods* (Kleinbaum & Kupper, 2013) was used as a theoretical basis for the quantitative part of the study.

4.4.1 Data cleaning

The questionnaire results were firstly exported from Qualtrics into an Excel worksheet, in order to have a starting database to work on the findings. Later, insights were collected regarding the number of finished survey sessions in relation to the total number of started sessions: a decision was taken to exclude from the results analysis only those survey attempts that were interrupted before or during the demographic section. The missing answers were later categorized as *missing values* in SPSS, with the aim of excluding them from the regressions. Attention check items were also analyzed, to check the potential presence of distracted answers. The survey sessions that contained responses not coherent with the attention item checks were excluded from the analysis.

4.4.2 Variables conversion

The categorical variables were converted into numerical ones to facilitate further analysis.
In particular:

- For the personality test, positive answers were assigned number +1, while negative answers were converted into number -1.

- For the *attitude* variable, every output was assigned a number from 1 to 5, on the basis of the answer given by each participant (specifically, for the positive answers, 1= *Strongly Disagree* and 5= *Strongly Agree;* for the negative answers, 1= *Strongly Agree* and 5= *Strongly Disagree*). Both in the case of *personality* and *attitude*, these conversions are the ones suggested by the authors of the scales.

- The answers expressing participants' frequency of use of AI tools in their academic paths were converted into numbers as well, according to the following scale:
  Very rarely = 1
  Rarely = 2
  Occasionally = 3
  Often = 4
  Very often = 5

- For the variable *gender*, dummy variables were created, on the basis of the three gender answers present in the database: *Female*, *Male* and *Prefer not to say*.

Specifically, *Dummy_Female, Dummy_Male* and *Dummy_Pref* were created, assuming the value 1 when positive.

The same reasoning was followed for the variables *nationality* and *residence*. Specifically:

- For the variable *nationality*, the dummy variables *Dummy_Italian, Dummy_French* and *Dummy_Othernat* were created.

- For the variable *residence*, the dummy variables *Dummy_Italy, Dummy_France* and *Dummy_Otherres* were created.

- For the *field of study*, two clusters were created, to permit a better analysis of the results. Subsequently, each cluster was assigned a number. Specifically, a group was structured, comprehending the scientific, medical and natural courses, these being: *Agriculture and Veterinary, Architecture, Engineering, Medicine and Surgery, Natural, Chemical and Physical Sciences, Computer Science and Technology, Agricultural, Food and Forestry Sciences* and *Technology*. This group was assigned the number 0 and was named *Cluster_Science*.
  The other cluster, containing humanistic and social courses, was formed by *Arts and Design, Economics and Statistics, Education and Training, Law, Humanities and Philosophy, Foreign Languages and Literatures, Psychology, Political and Social Sciences, Humanities, Sports and Physical Education* and *Tourism*. This group was assigned the number 1 and was named *Cluster_Human*.
  A dummy variable was created for one of these clusters, and named *Dummy_Science.*
  The other cluster was consequently represented when *Dummy_Science* = 0.
  For the answers reporting *Other*, every individual text entry in the designated box was checked and assigned to one of the two clusters on the basis of the strongest affinity.

- Finally, the following questions only presented *Yes* and *No* as possible answers. These latter were transformed into numerical outputs, with *Yes*= 1 and *No*= 0:
  Have you ever used Artificial Intelligence tools during your academic journey?
  Do you have any concerns about the use of Artificial Intelligence within your academic journey?

4.4.3 Interpretation of *personality traits* results

For what regards the data obtained with the Eysenck scale, for personality traits (Eysenck, 1958), results were interpreted following the indications given by the author of the scale. Specifically, as anticipated in sub-paragraph 4.4.2, the positive answers to the attitude affirmations were assigned a +1 and the negatives a -1, respectively to the neuroticism or extraversion score, on the basis of the type of question. The scheme followed for this purpose is presented in Figure 9.

Figure 9. *Division of the questions of Eysenck's short test*

Questions	***Key***
Do you sometimes feel happy, sometimes depressed, without any apparent reason?	N
Do you prefer action to planning for action?	E
Do you have frequent ups and downs in mood, either with or without apparent cause?	N
Are you happiest when you get involved in some project that calls for rapid action?	E
Are you inclined to be moody?	N
Does your mind often wander while you are trying to concentrate?	N
Do you usually take the initiative in making new friends?	E
Are you inclined to be quick and sure in your actions?	E
Are you frequently "lost in thought" even when supposed to be taking part in a conversation?	N
Would you rate yourself as a lively individual?	E
Are you sometimes bubbling over with energy and sometimes very sluggish?	N
Would you be very unhappy if you were prevented from making numerous social contacts?	E

Note: N stands for neuroticism, while E stands for extraversion

Source: Based on Eysenck, 1958

It has to be noted how the attention check item inserted by the researcher is not present in this scale, and was not considered during the grading of the answers. This item was just considered in the previous part of the analysis, to check the participants' compliance with it.

4.4.4 Interpretation of *attitude towards AI* results

A similar interpretation work was also conducted for the results obtained with the GAAIS scale, measuring participants' attitude towards AI (Schepman & Rodway, 2023). In this case, the authors of the scale offered a precise set of instructions to be followed for the scoring, as reported in Figure 10. A part from the attention check item, which compliance was already controlled in the previous part of the analysis, and then excluded from this scoring, the results of the GAAIS scale questions were converted as anticipated in sub-paragraph 4.4.2, hence in the following way: firstly, positive and negative items' columns were separated within the Excel sheet, and two additional columns were created at the end of every subset of affirmations. Later, every answer was assigned a score from 1 to 5 (with 1= *Strongly Disagree* and 5= *Strongly Agree* for the positive affirmations, and an inverse scale for the negative ones). Subsequently, the means were calculated for both the positive and the negative set of items, and inserted in the two blank columns previously created. As described by the authors of the scale, the obtained values represent a more positive attitude towards AI the higher they are. Since the authors of the GAAIS explicitly discourage calculating an overall scale mean, a decision was taken to sum the two means calculated, with the aim of obtaining a single set of values to work on, for data analysis purposes.

Figure 10. *Scoring instructions for the GAAIS scale by Schepman and Rodway*

Subscale (Not for display)	*Number (not for display)*	*Item*
Positive	1	For routine transactions, I would rather interact with an artificially intelligent system than with a human
Positive	2	Artificial Intelligence can provide new economic opportunities for this country
Negative	3	Organizations use Artificial Intelligence unethically
Positive	4	Artificial Intelligence systems can help people feel happier

Positive	5	I am impressed by what Artificial Intelligence can do
Negative	6	I think artificially intelligent systems make many errors
Positive	7	I am interested in using artificially intelligent systems in my daily life
Negative	8	I find Artificial Intelligence sinister
Negative	9	Artificial Intelligence might take control of people
Negative	10	I think Artificial Intelligence is dangerous
Positive	11	Artificial Intelligence can have positive impacts on people's wellbeing
Positive	12	Artificial Intelligence is exciting
Attention Check	**A**	**I would be grateful if you could select Strongly Agree**
Positive	13	An artificially intelligent agent would be better than an employee in many routine jobs
Positive	14	There are many beneficial applications of Artificial Intelligence
Negative	15	I shiver with discomfort when I think about future uses of Artificial Intelligence
Positive	16	Artificially Intelligent systems can perform better than humans
Positive	17	Much of society will benefit from a future full of Artificial Intelligence
Positive	18	I would like to use Artificial Intelligence in my own job
Negative	19	People like me will suffer if Artificial Intelligence is used more and more
Negative	20	Artificial Intelligence is used to spy on people
Scoring: Check compliance with the Attention Check, then discount it from the scoring. Score items marked "Positive" as Strongly Disagree= 1; Disagree= 2; Neutral = 3; Agree = 4; Strongly Agree = 5. Score the items marked "Negative" in reverse so that Strongly Disagree = 5; Disagree = 4; Neutral = 3; Agree = 2; Strongly Agree = 1. Then take the mean of the positive items to form an overall score for the positive subscale, and the mean of the negative items to form the negative subscale. The higher the score on each subscale, the more positive the attitude. We do not recommend calculating an overall scale mean.		

Source: Based on Schepman and Rodway, 2023

4.4.5 Harman's test

The next step followed during the quantitative phase of the study consisted of the conduction of the Harman's single factor test, which was run on SPSS with the aim of testing for common method biases (Podsakoff *et al.*, 2003). Specifically, the variables involved in this analysis were *personality*, *attitude towards AI*, *frequency of use* and *level of satisfaction*. A decision was taken to analyze only these variables, because the other factors measured were not considered to be possibly influenced by common method bias. It has to be taken into account that the participants' responses that lacked answers for one or more of the analyzed variables were excluded by the Harman's test. After this preliminary data manipulation, the test was run on SPSS, and the *total variance explained* results were observed for the assessment of the potential presence of common method bias.

4.4.6 Multiple choice questions' analysis

Inside the survey, the questions providing a multiple choice answer regarded the students' *areas of use of AI* and their potential *concerns* about these tools. Their results were analyzed to obtain the percentages of selection of each option.

4.4.7 Open questions analysis

The survey also presented two open questions:
What are the reasons why you have never used such tools?
What tools do you use specifically? (You can indicate more than one)
The answers to these questions were examined through a coding process.

4.4.8 *Satisfaction* and *Frequency of use* analysis

The results of the two questions on the satisfaction level of the participants and their frequency of use of AI tools were analyzed with the aim of understanding the general trends of the sample in these terms. Specifically, descriptive statistics were investigated.

4.4.9 Statistical analyses, regressions and assumptions checks

For the central part of the quantitative section of the study, statistical analyses were run with the aim of testing the hypotheses of the case (See Figure 8).
Depending on the structure of every hypothesis, the method applied for their testing was chosen among One Way ANOVA, t-test and linear regressions. In particular, after every

regression, attention was paid to the possible presence of issues that could compromise the validity of the results. The following aspects were investigated:

- Absence of multicollinearity
- Normality of residuals
- Linearity
- Homoscedasticity

The results of these analyses are described in the Results section.

4.5 Interviews Structure

The interviews aimed to gain additional, more extensive insights on the research questions' topics, as well as addressing new potential queries emerging from the survey outcomes.
Literature was consulted to determine the interviews' characteristics and structure.

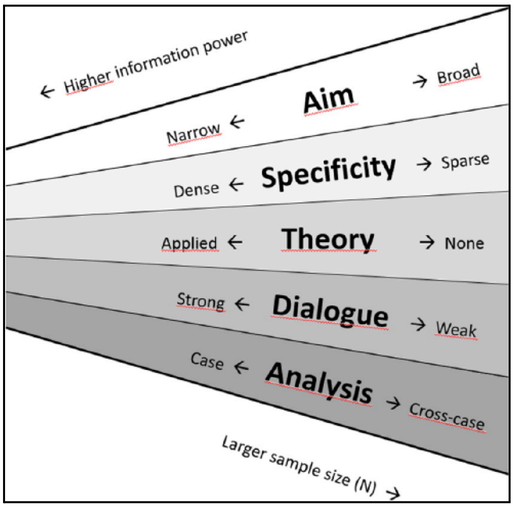
4.5.1 Sample selection

A choice was made to adopt Malterud, Siersma and Guassora's study (2016) to select the sample size, following the *information power concept*, according to which the more information a sample holds, the less participants are needed, and the saturation of the sample amount is not necessary to gain relevant insights for the research (Malterud *et al.*, 2016).
The guidelines offered by the aforementioned research suggest to choose the sample size for qualitative interviews based on:

- the broadness of the aim of the study
- the specificity of the interviewees with respect to the aim of the study
- the possible presence of a theoretical framework to support the study
- the quality of the interview dialogue
- the possible structure of the study as a cross-case analysis

Figure 11 reports the schematic representation of this concept.

Figure 11. *Items and dimensions within the information power concept*



Source: Malterud *et al.*, 2016

Considerations were made on the research starting from this model. The study's aim was evaluated as more directed towards being broad, based on the presence of two research questions and their individual scope. Additionally, the structure of the research naturally led it to being a cross-case analysis, increasing the expected sample size. On the other hand, the interviews were considered vastly specific, with the interviewees being the main subjects of the study and the key source to answer the research questions. Moreover, the presence of a strong theoretical framework behind the research, and the possibility to create strong interview dialogues, furtherly enhanced the information power of the sample, reducing the target sample size.

This evaluation of the study structure led to the decision of conducting at least twelve interviews, intended to be divided as fairly as possible among the study population, within the constraints of the convenience sampling. When possible, scholars within the same University were chosen from different fields of study, to enhance the specificity of the sample.

In any case, the adequacy of the sample was continuously evaluated during the research process, based on the results obtained and the consequent amount of information useful to the aim of the study (Malterud *et al.*, 2016).

4.5.2 Content of the interviews

Interviews were given an overall equal structure, with macro topics to be addressed with all the interviewees. The main matters explored in the interviews regarded the participants' relationship with technology, their use of AI at university and their opinions with this regard. Figure 12 summarizes the steps planned to be followed within every interview, the related questions and their purpose for the study.

Figure 12. *Framework followed for the interviews*

STEPS OF THE INTERVIEW	*QUESTIONS POSED*	*SCOPE WITHIN THE RESEARCH AIM*
0 - Anonymity declaration and consent request	Interviewees were informed that their responses would be anonymously recorded, and they were asked for their consent to use their answers for the study's purpose	• Guarantee transparency • Reduce the potential impact of the social desirability bias • Improve the quality of the results
1 - General presentation	1) What gender do you identify with? 2) How old are you? 3) Which country are you from? 4) Where do you live?	• Demographic collocation of the sample units • Useful for comparisons between groups of interviewees
2 - Academic career	1) In which country are you studying? 2) Which university do you attend? 3) What is your field of study? 4) What level of study are you currently pursuing?	• Academic collocation of the sample units • Useful for comparisons between groups of interviewees

3 - Use of Technology	1) Are you familiar with technology? 2) What is the use you make of technological devices and tools during your day? 3) In what moments of your day do you use technology the most? For which purposes? 4) What tools do you use at university, to help you with the study in general?	Introducing the main topics of the interview, understanding the relationship of sample units with technology in general
4 - Use of AI	1) How much do you feel informed about AI? How would you describe it in your own words? 2) Are you familiar with Artificial Intelligence tools? If so, which ones do you use, and for what purposes? 3) Do artificial intelligence tools help you within your academic journey? If so, how do you use them and which ones	Understanding the role given to AI in everyday life and within the academic context

	do you prefer? If not, why?	
5 - Opinion, perception and potential concerns	1) What is your opinion with regard to these tools? Are you satisfied with them? 2) Do you have concerns with regard to the use of AI in your academic journey? If so, about what? 3) Where did these concerns originate? 4) Do you think that stricter regulations are needed for AI in the educational context?	● Examining the perception of the sample towards AI ● Exploring potential concerns and their source
6 - Potential new questions that arose after the survey results' analysis		Enhancing the research's completeness and improving the integration between quantitative and qualitative methodology

Source: Author's work

Given the intent to potentially explore new themes that emerged after the analysis of the survey results, interviews were conducted in a later phase of the study, following the collection of the survey responses. Specifically, after obtaining the survey results, no need for the insertion of other questions was found, yet a decision was taken to focus on the choice of

the sample for interviews. In fact, the survey results highlighted an imbalance inside the sample in terms of gender and field of study of the participants. Therefore, when selecting interviewees, emphasis was placed on achieving a more diverse sample for the interviews.
The interviewees were given the possibility to choose between Italian and English as languages for the interview conduction, in order to facilitate a more comfortable interaction, within the limits of the language capacities of the researcher.
The interviewees were also given the possibility to span freely across different topics, also exceeding the interviewer's questions, with the aim of avoiding any constraints to their expression and to gain any additional important information.
In terms of method, it should be noted how some of the interviews were conducted through the Zoom platform, others in person, and some in written form, based on the availability of the interviewees. The interviewees were informed of the anonymity of the responses record and, for those who accorded for an oral interview, permission was explicitly requested for the audiotaping of the dialogues. In these latter cases, it was highlighted how these audio recordings were only used for the purpose of writing the transcripts of the interviews. The collected data was stored securely, and accessed only to the researcher. Finally, all of the interviewees were asked for the consent of using their answers for the aim of the research.

4.6 Steps for the Analysis of the Interviews' Results

4.6.1 Interviews participants' demographics and academic characteristics

As previously mentioned, the interviewees for this study were chosen with a convenience sampling, yet trying to reach a sample as diversified as possible, in order for it to be more representative of the population. The demographic and academic characteristics of the sample were firstly analyzed, with the aim of gaining a better vision on the specificities of the interviewees.

4.6.2 Transcription and translation

The analysis of the results was preceded by a series of peculiar passages, aimed at reaching the best organization for the collected data, and consequently facilitating their interpretation.
The first step consisted of the transcription of the audio recorded interviews into text format.
Subsequently, the dialogues that were conducted in Italian were translated to English, in order to ensure a better data comparability.

4.6.3 Coding process

Later, the data analysis was executed. Interviews' outcomes were analyzed starting from a thorough coding process, divided into two cycles (Rogers, 2018; Gupta, 2024). Both phases were conducted with the help of an Excel sheet, where the interviews' content was organized on the basis of the codes and of the demographic information of the participants. During the first coding phase, the main themes and recurring concepts were delineated and codes were assigned to them; subsequently, another screening of the transcripts was conducted with the aim of reanalyzing data, possibly changing codes, inserting new ones or collecting more codes into macro areas (Rogers, 2018). Within this second part of the analysis, codes were then investigated with the aim of finding patterns, similarities or differences among the participants' responses, delineating the results of the qualitative part of the study.

The analysis of the interviews' outcomes, which was done following this methodology, is reported in the results section of this research.

5. Results of the Study

5.1 Results of the Survey

5.1.1 Harman's test on common method bias

Harman's test on common method bias wan run, following the passages explained in the methodology section, sub-paragraph 4.4.3. The first factor showed to represent the 19.49% of the total variance explained (See Figure 13). This value was retained to be acceptable to exclude the possibility of a common method bias influence of the survey results.

Figure 13. *Total variance explained in the survey results*

Total variance explained

Factor	Initial eigenvalues			Extraction sums of squared loadings		
	Total	% of variance	cumulative %	Total	% of variance	cumulative %
1	7.017	19.490	19.490	6.350	17.639	17.639
2	4.035	11.209	30.699			
3	2.658	7.384	38.083			
4	1.833	5.092	43.176			
5	1.720	4.778	47.953			
6	1.473	4.091	52.044			
7	1.354	3.761	55.805			
8	1.238	3.438	59.243			
9	1.150	3.194	62.437			
10	1.058	2.939	65.375			
11	0.994	2.760	68.135			
12	0.943	2.618	70.753			
13	0.910	2.527	73.280			
14	0.841	2.337	75.618			
15	0.819	2.275	77.893			
16	0.764	2.121	80.014			
17	0.733	2.036	82.049			
18	0.612	1.700	83.749			
19	0.565	1.570	85.319			
20	0.521	1.446	86.766			
21	0.495	1.375	88.140			
22	0.471	1.309	89.449			
23	0.456	1.268	90.717			
24	0.431	1.198	91.915			
25	0.411	1.143	93.058			
26	0.371	1.029	94.087			
27	0.343	0.952	95.040			
28	0.315	0.876	95.916			
29	0.287	0.798	96.714			
30	0.258	0.718	97.432			
31	0.212	0.589	98.021			
32	0.190	0.527	98.548			
33	0.163	0.453	99.000			
34	0.145	0.402	99.402			
35	0.124	0.344	99.745			
36	0.092	0.255	100.000			

Extraction method: Principal Axis Factoring

Source: Author's work

5.1.2 Demographics' analysis

After the data cleaning process, which methodology was illustrated in sub-paragraph 4.4.1, a total of 124 answers were examined.

The first step in the analysis of the survey's results focused on the appraisal of the demographic characteristics of the sample units.

The descriptive statistics for the demographic variables are summarized in Figure 14 and Figure 15. It was found that the sample contained a predominance of units of female gender, as well as units with Italian nationality and Italian residence.

Figure 14. *Descriptive statistics for the variables nationality, residence and gender*

Variable	Category	Frequency	Percentage
Nationality	Italian	88	70.97%
	French	21	16.94%
	Other	15	12.1%
Residence	Italy	93	75.00%
	France	27	21.77%
	Other	4	3.23%
Gender	Male	39	31.45%
	Female	83	66.94%
	Prefer not to say	2	1.61%

Source: Author's work

Figure 15. *Descriptive statistics for the variable age*

Variable	Mean	Standard Deviation	Min	Max	N
Age	22.57	2.85467349548091	18	32	124

Note: M = Mean; SD = Standard Deviation; Min = Minimum; Max = Maximum; N = Number of Participants

Source: Author's work

5.1.3 Academic characteristics of the respondents

The information set regarding the academic characteristics was analyzed as well. Descriptive statistics were calculated for the university and the field of study among the respondents (See

Figure 16, Figure 17 and Figure 18). It has to be noted how, for the 30 responses "*Other*", the written answers that participants gave in the dedicated text entry box were consulted, finding how 5 of these units were enrolled in other French universities, while the rest to various Italian ones.

For what regards the field of study, diversities were found in these responses as well, with a set of answers highly skewed towards *Economics and Statistics*, these being 41 in total. Responses from the field of *Medicine and Surgery* were found higher than the rest as well. Moreover, very few answers were collected by students enrolled in the courses of *Law*, *Computer Science and Technology* and *Architecture*. A peculiarity of this variable's responses also regards the elevated number of participants selecting the option *Other*. However, the answer that these participants provided in the text entry box gave the researcher the opportunity to categorize their field of study in one of the two clusters created for the analysis without difficulty.

Figure 16. *Descriptive statistics for the variable University of enrollment*

Category	Frequency	Percentage
UniPG	54	45.38%
ISG Paris	23	19.33%
LUISS	12	10.08%
Other	30	25.21%
Total	119	

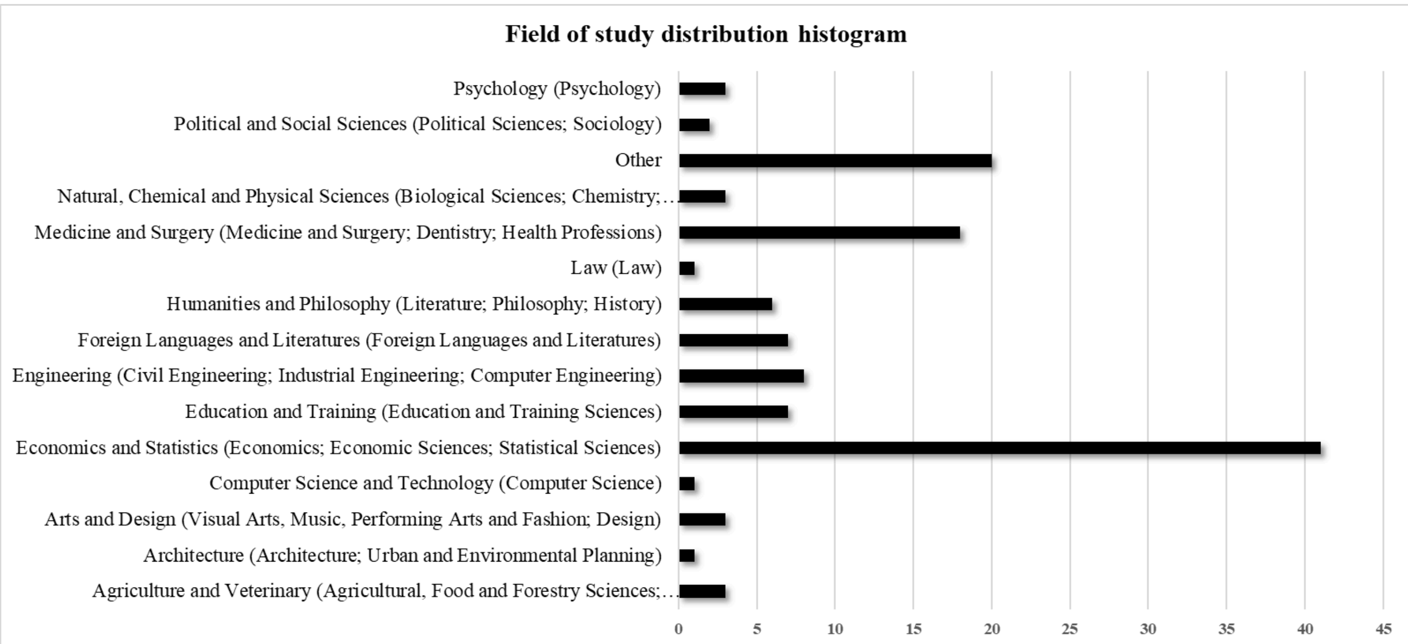
Source: Author's work

Figure 17. *Descriptive statistics for the Field of study variable among the participants*

Category	Frequency	Percentage
Agriculture and Veterinary	3	2.42%
Architecture	1	0.81%
Arts and Design	3	2.42%
Computer Science and Technology	1	0.81%
Economics and Statistics	41	33.06%
Education and Training	7	5.65%
Engineering	8	6.45%
Foreign Languages and Literatures	7	5.65%
Humanities and Philosophy	6	4.84%
Law	1	0.81%
Medicine and Surgery	18	14.52%
Natural, Chemical and Physical Sciences	3	2.42%
Other	20	16.13%
Political and Social Sciences	2	1.62%
Psychology	3	2.42%
Grand Total	124	

Source: Author's work

Figure 18. *Distribution of the field of study among the respondents*



Source: Author's work

5.1.4 Personality results interpretation

The results of the survey sections regarding personality were analyzed, with the aim of delineating the general characteristics of the sample in these terms. Figure 19 shows the descriptive statistics for the *Personality* variable. The category *Equal* refers to those sample units who scored the same points for neuroticism and extraversion, and consequently do not present a dominant trait.

Figure 19. *Descriptive statistics for the variable Personality*

Variable	Category	Frequency	Percentage
Personality	Neurotic	75	60.48%
	Extraverted	35	28.23%
	Equal	14	11.29%
Total		124	

Source: Author's work

5.1.5 *Satisfaction* and *Frequency of use* analysis

91 participants answered the two questions regarding their satisfaction level with respect to AI tools and the frequency of their use for academic purposes. For the variable *Frequency of use*, the analysis was run based on the converted answers, as anticipated in the methodology section. Firstly, descriptive statistics for both variables were calculated (See Figure 20). Later, the results were analyzed, and for the variable *Frequency of use* a prevalence of answers *Occasionally* and *Often* was found, while the option *Rarely* was the least chosen one (See Figure 21)

For what regards the satisfaction level of participants, instead, none of the units selected the options 1 or 2. Moreover, the results were skewed towards the positive scores, with 7 being the most selected option (See Figure 22).

Figure 20. *Descriptive statistics regarding participants' frequency of use of AI tools for academic purposes and their satisfaction level*

Variable	Mean	Standard Deviation	Min	Max	N
Frequency of use	3.23	1.13170358410318	1	5	91
Satisfaction level	7.04	1.41352269102636	3	10	91

Note: M = Mean; SD = Standard Deviation; Min = Minimum; Max = Maximum; N = Number of Participants

Source: Author's work

Figure 21. *Frequency of answers for the variable Frequency of use*

Options	Frequency	Percentage
1	12	13.20%
2	9	9.89%
3	34	37.36%
4	26	28.57%
5	10	10.99%
Grand Total	91	

Source: Author's work

Figure 22. Frequency of answers regarding the satisfaction level of the participants

Satisfaction level	Frequency	Percentage
3	1	1.10%
4	3	3.30%
5	6	6.59%
6	19	20.9%
7	31	34.1%
8	20	22.0%
9	5	5.50%
10	6	6.59%
Grand Total	91	

Source: Author's work

5.1.6 Correlations among variables

Figure 23 reports the correlations for the analyzed variables, comprehensive of the interaction variables that were created for the purpose of the study. For the categorical variables, this table was created using their respective dummies.

Correlations

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)
Dummy_Female (1)	1.00	-0.182*	-0.964**	-0.15	0.04	-0.13	0.12	0.16	0.03	-0.17	-0.395**	-0.268*	-0.14	-0.14	0.10	0.17	-0.09	0.00	-0.14	0.385**	-0.225*	0.09
Dummy_Prefer not to say (2)	-0.182*	1.00	-0.09	-0.06	-0.06	-0.07	0.09	0.15	-0.02	0.02	0.14	0.18	0.00	-0.08	0.17	0.06	0.07	0.00	-0.01	-0.07	-0.02	0.202*
Dummy_Male (3)	-0.964**	-0.09	1.00	0.17	-0.03	0.15	-0.15	-0.198*	-0.03	0.17	0.361**	0.217*	0.14	0.17	-0.15	-0.184*	0.07	0.00	0.14	-0.371**	0.233**	-0.14
Dummy_Italian (4)	-0.15	-0.06	0.17	1.00	-0.706**	0.903**	-0.825**	-0.580**	-0.285**	0.273**	-0.225*	-0.273**	-0.225*	0.313**	-0.11	-0.11	-0.11	-0.10	-0.02	-0.07	-0.07	-0.12
Dummy_French (5)	0.04	-0.06	-0.03	-0.706**	1.00	-0.782**	0.752**	-0.17	0.16	-0.310**	0.299**	0.273**	0.04	-0.229*	0.11	0.17	0.06	0.07	0.01	0.12	0.13	0.13
Dummy_Italy (6)	-0.13	-0.07	0.15	0.903**	-0.782**	1.00	-,914**	-0.357**	-0.316**	0.326**	-0.263**	-0.253*	-0.13	0.271**	-0.07	-0.198*	-0.10	-0.10	0.01	-0.16	-0.08	-0.09
Dummy_France (7)	0.12	0.09	-0.15	-.825**	.752**	-.914**	1.00	.284**	-0.10	-.319**	.197*	.257*	0.05	-.280**	0.13	.223*	0.03	0.03	-0.03	.213*	0.05	0.15
Dummy_Other nationality (8)	0.16	0.15	-.198*	-.580**	-0.17	-.357**	.284**	1.00	.213*	-0.02	-0.03	0.06	.255*	-0.17	0.03	-0.05	0.09	0.06	0.02	-0.04	-0.06	0.02
Dummy_Other residence (9)	0.03	-0.02	-0.03	-.285**	0.16	-.316**	-0.10	.213*	1.00	-0.05	0.18	0.02	0.18	-0.01	-0.14	-0.03	0.17	.177*	0.04	-0.10	0.09	-0.14
Age (10)	-0.17	0.02	0.17	.273**	-.310**	.326**	-.319**	-0.02	-0.05	1.00	.261**	.242*	0.19	0.06	-.252**	-.259**	-0.02	0.03	-0.09	-0.18	-.184*	-.244**
Attitude (11)	-.395**	0.14	.361**	-.225*	.299**	-.263**	.197*	-0.03	0.18	.261**	1.00	.535**	.368**	0.03	-.190*	-0.02	0.07	0.12	-0.08	-0.12	0.10	-0.14
Frequency of use (12)	-.268*	0.18	.217*	-.273**	.273**	-.253*	.257*	0.06	0.02	.242*	.535**	1.00	.321**	-0.03	-0.18	0.13	0.06	0.09	-0.05	0.07	0.07	-0.16
Satisfaction (13)	-0.14	0.00	0.14	-.225*	0.04	-0.13	0.05	.255*	0.18	0.19	.368**	.321**	1.00	0.00	-.392**	-0.02	-0.02	-0.04	0.02	-0.07	0.07	-.372**
Dummy_Science (14)	-0.14	-0.08	0.17	.313**	-.229*	.271**	-.280**	-0.17	-0.01	0.06	0.03	-0.03	0.00	1.00	-0.13	-.177*	-0.06	-0.03	-0.06	-0.07	-0.17	-0.12
Concerns (15)	0.10	0.17	-0.15	-0.11	0.11	-0.07	0.13	0.03	-0.14	-.252**	-.190*	-0.18	-.392**	-0.13	1.00	.321**	-0.04	-0.01	-0.07	.212*	.195*	.995**
Neuroticism (16)	0.17	0.06	-.184*	-0.11	0.17	-.198*	.223*	-0.05	-0.03	-.259**	-0.02	0.13	-0.02	-.177*	.321**	1.00	-0.15	-0.14	-0.07	.787**	.533**	.328**
Extraversion (17)	-0.09	0.07	0.07	-0.11	0.06	-0.10	0.03	0.09	0.17	-0.02	0.07	0.06	-0.02	-0.06	-0.04	-0.15	1.00	.833**	.541**	-0.17	-0.02	-0.03
FemalexExt (18)	0.00	0.00	0.00	-0.10	0.07	-0.10	0.03	0.06	.177*	0.03	0.12	0.09	-0.04	-0.03	-0.01	-0.14	.833**	1.00	0.00	-0.17	0.00	0.00
MalexExt (19)	-0.14	-0.01	0.14	-0.02	0.01	0.01	-0.03	0.02	0.04	-0.09	-0.08	-0.05	0.02	-0.06	-0.07	-0.07	.541**	0.00	1.00	-0.05	-0.04	-0.08
FemalexNeu (20)	.385**	-0.07	-.371**	-0.07	0.12	-0.16	.213*	-0.04	-0.10	-0.18	-0.12	0.07	-0.07	-0.07	.212*	.787**	-0.17	-0.17	-0.05	1.00	-0.09	.207*
MalexNeu (21)	-.225*	-0.02	.233**	-0.07	0.13	-0.08	0.05	-0.06	0.09	-.184*	0.10	0.07	0.07	-0.17	.195*	.533**	-0.02	0.00	-0.04	-0.09	1.00	.206*
AttitudexConcerns (22)	0.09	.202*	-0.14	-0.12	0.13	-0.09	0.15	0.02	-0.14	-.244**	-0.14	-0.16	-.372**	-0.12	.995**	.328**	-0.03	0.00	-0.08	.207*	.206*	1.00

*. Correlation is significant at the 0.05 level (2-tailed).

**. Correlation is significant at the 0.01 level (2-tailed).

Figure 23.

Pearson table of the correlations between the variables of the study

Source: Author’s work

5.1.7 Qualitative questions analysis: reasons of no use and concerns

As shown in the methodology section, the frequency of answers in the closed qualitative questions was investigated, and open questions were analyzed as well through a coding process, with the aim of obtaining additional important data for the study. The analysis followed the questions' order in the survey, starting from the following questions:

1. *Have you ever used Artificial Intelligence tools during your academic journey?*
2. *If you answered no, what are the reasons why you have never used such tools?*
3. *Do you have any concerns about the use of Artificial Intelligence within your academic journey?*
4. *If so, which concerns do you have?*

The number of analyzed responses resulted to be smaller than the initial sample, due to the participants that left the survey before its end, resulting in a final count of 114.

What specifically emerged from the study of these answers can be summarized in the following key points:

- 80.70% of the participants reportedly had already used AI tools during their academic journey, at the time of the survey
- Among the survey units that never used AI tools before, the main reasons of no-use that were highlighted are represented by *the lack of necessity to use them, the personal preference to work without external aids, the personal will to only work with paper materials and books*, and *the scarce knowledge about the capabilities of these tools.*
- 39.82% of the participants affirmed to have concerns regarding the use of AI tools for academic purposes. Specifically, the main preoccupation of this part of the sample regards the overreliance and dependency to the tools. Reliability and accuracy of results were found to be another aspect of worry, as well as the lack of privacy and data security. The participants also highlighted their concerns in terms of the lack of interpersonal connection, the potential presence of biases and the fear of being penalized. A few answers also regarded the worry of a possible Internet addiction consequent to the use of these tools, and concerns regarding their costs and general accessibility. Nine participants stated to have other preoccupations as well, yet only five of them specified it in the dedicated text entry box in the survey.

One unit affirmed to work as a graphic illustrator, and expressed a concern regarding the possibility for AI to replace this job in the future; another participant affirmed to be worried about a misuse of these tools for academic exams, obtaining a degree without merit. An additional open response to this question focused on the risk for humans to apply AI answers and suggestions to human behaviors. Finally, two participants underlined the strong polluting effect of Artificial Intelligence servers' maintenance.

Figure 24 shows the frequency of every answer among the sample. For the interpretation of this table it has to be taken into account how every participant had the possibility to choose more than one option, hence the sum of the frequencies does not coincide with the sample units.

Figure 24. *Frequency of answers regarding participants' concerns about AI tools*

Concerns regarding the use of AI tools	
Reliability and accuracy of the results	25
Overreliance and dependency	29
Ethical Implications	23
Lack of privacy and data security	20
Lack of Interpersonal connection	16
Presence of biases	15
Fear of being penalized	13
Internet addiction	8
Costs and accessibility	6
Other	5

Source: Author's work

5.1.8 Qualitative questions analysis: tools used and areas of application

Later, the analysis of the qualitative questions proceeded, by investigating the results of the following:

1. *What tools do you use specifically? (You can indicate more than one)* (open question)
2. *Please select the areas in which you use Artificial Intelligence for University* (multiple choice question)

Also in this case, the analyzed answers' amount was reduced from the previous section because of the dropout of several participants, resulting in a final count of 91.

In terms of tools, the findings showed similarities among the sample (see Figure 25):

- The most common answer was ChatGPT, with 81 out of 91 participants mentioning it among the AI tools they use for academic purposes, followed by Gemini and Microsoft Copilot. This result shows a predominance in the choice of virtual assistants and chatbots.
- A few participants also stated to be using AI models dedicated to text generation, like Llama, Mistral AI, Suno and Grammarly, or translation, like Reverso and DeepL Translate
- Other units mentioned tools for intelligent reading and text comprehension, such as Wisdolia, Consensus and ChatPDF
- Among the received answers, few of them also referred to the use of tools for the generation of images and creative contents, like DALL-E, Gamma and Midjourney

Figure 25 *Frequency of answers regarding the AI tools used by participants*

AI tools used by the sample	
ChatGPT	81
Gemini	13
Microsoft Copilot	6
Perplexity	2
Llama	2
Mistral AI	2
DeepL Translate	2
ChatPDF	2
Wisdolia	1
DeepAI	1
AI chats	1
Suno	1
Ad hoc neural networks	1
DALL-E	1
Gamma	1
Notion AI	1
Grammarly	1
Reverso	1
Consensus	1
OpenAI	1
Midjourney	1
Intelligent tools for the creation of Powerpoints	1
Chai AI	1
AI tools for the creation of images	2

Source: Author's work

For what regards the applications of these tools, 62 out of 91 participants stated to use AI tools for research assistance, yet many answers were also collected regarding different applications: the most mentioned ones, specifically, were found to be the clarification of questions and concepts, the summary and organization of large amounts of data or the correction of grammatical errors and improvement of style in text inputs. However, several participants also reported to use AI tools for other purposes, like exams preparation, problem solving, coding and programming assistance and for the creation of videos, images or presentations (See Figure 26).

Figure 26. *Frequency of answers regarding participants' areas of applications of AI tools in academic contexts*

Sample's areas of use of AI in academic contexts	
For research assistance	62
To clarify questions or explain specific concepts	52
To summarize, organize or analyze large amounts of data	47
As a writing aid	44
For translations	27
For exams preparation	23
For text analysis or text generation	22
For problem solving or decision making	19
For coding assistance, programming and simulations	14
For assisted creation of videos, images or presentations	12

Source: Author's work

5.1.9 Statistical analyses and regressions

As anticipated in the methodology section, linear regressions were run to test the hypotheses of the study, and specific aspects were investigated to check the validity of their results.

- *Hypothesis 1:* Students' attitude towards Artificial Intelligence tools differs based on their field of study.

A t-test was run in order to compare the means of Attitude towards AI within the group *Dummy_Science*, for condition 0 and 1, with 1 representing the belonging of the sample unit to the scientific cluster for fields of study. The confidence interval for this analysis was set at 95%.

The t-test resulted in a t value of -0.349 with 112 degrees of freedom, assuming equal variances. Moreover, the corresponding p-value was 0.765 (see Figure 27): hence, not enough statistical evidence was found to reject the null hypothesis, since the p-value was higher than the 0.05 significance level. Consequently, *Hypothesis 1* could not be accepted based on these results.

Figure 27. *Independent Samples Test for Hypothesis 1*

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means							
		F	Sig.	t	df	Significance		Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
						One-Sided p	Two-Sided p			Lower	Upper
Attitude	Equal variances	0.090	0.765	-0.349	112	0.364	0.728	-0.05126	0.14678	-0.34209	0.23957
	Equal variances not			-0.359	59.949	0.360	0.721	-0.05126	0.14283	-0.33696	0.23445

Source: Author's work

- *Hypothesis 2*: Gender influences students' attitude towards AI

The testing of *Hypothesis 2* was controlled for *age* and *nationality*, on the basis of the pre-existing literature on similar topics, which showed relationships between these variables and students' attitude toward AI or, more generally, technology. All of the variables, except for *Dummy_Italian*, were shown to have a significant relationship with *Attitude towards AI* (See Figure 28). The ANOVA table was consulted as well, showing a total regression significance $p < 0.001$ and consequently providing strong evidence to reject the null hypothesis (See Figure 29). An adjusted R^2 of 31.7% also suggests that the model is more representative of the changes of the dependent variable when it considers the control variables, with respect to when it does not (adjusted R^2 = 20.2%) (See Figure 30). Subsequently, the values of standardized β for the dummies were analyzed (See Figure 28). The three dummy variables for gender were found to have an effect on the students' attitude towards AI, with males (standardized β = 0.333), and individuals that chose the option *prefer not to say* (standardized β = 0.176), having a more positive attitude towards AI with respect to women (baseline of the model).

Figure 28. *Coefficients of the regression ran to test Hypothesis 2*

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients			95,0% Confidence Interval for B		Collinearity Statistics	
		B	Std. Error	Beta	t	Sig.	Lower Bound	Upper Bound	Tolerance	VIF
1	(Constant)	5.065	0.528		9.598	0.000	4.019	6.111		
	Age	0.096	0.022	0.383	4.348	0.000	0.052	0.140	0.912	1.096
	Dummy_Italian	-0.091	0.182	-0.059	-0.503	0.616	-0.451	0.269	0.508	1.970
	Dummy_French	0.692	0.224	0.369	3.085	0.003	0.247	1.136	0.493	2.027
2	(Constant)	5.380	0.497		10.828	0.000	4.395	6.365		
	Age	0.078	0.021	0.309	3.713	0.000	0.036	0.120	0.872	1.147
	Dummy_Italian	-0.176	0.173	-0.114	-1.018	0.311	-0.519	0.167	0.479	2.088
	Dummy_French	0.604	0.212	0.322	2.844	0.005	0.183	1.025	0.470	2.128
	Dummy_Pref	0.937	0.420	0.176	2.232	0.028	0.105	1.769	0.970	1.030
	Dummy_Male	0.497	0.121	0.333	4.089	0.000	0.256	0.737	0.911	1.098

a. Dependent Variable: ATTITUDE

Source: Author's work

Figure 29. *ANOVA table for Hypothesis 2*

ANOVA						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	12.422	3	4.141	10.548	<.001b
	Residual	43.181	110	0.393		
	Total	55.604	113			
2	Regression	19.322	5	3.864	11.503	<.001c
	Residual	36.282	108	0.336		
	Total	55.604	113			

a Dependent Variable: ATTITUDE
b Predictors: (Constant), Dummy_French, Age, Dummy_Italian
c Predictors: (Constant), Dummy_French, Age, Dummy_Italian, Dummy_Pref, Dummy_Male

Source: Author’s work

Figure 30. *Summary of the model used for the testing of Hypothesis 2*

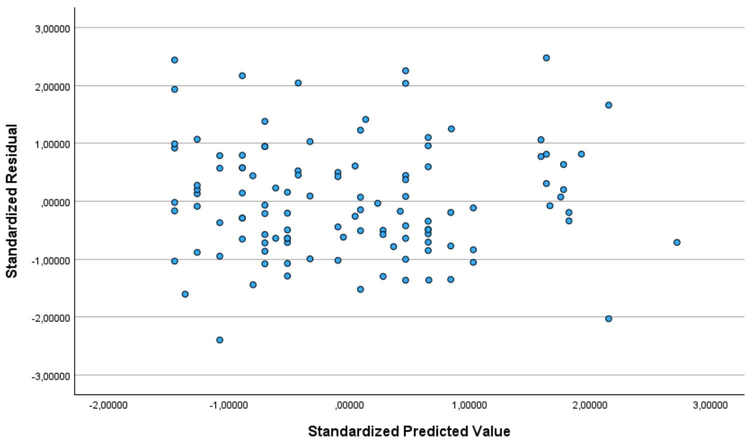
Model Summary[c]					Change Statistics					
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	0.473[a]	0.223	0.202	0.62654	0.223	10.548	3	110	0.000	
2	0.589[b]	0.347	0.317	0.57960	0.124	10.269	2	108	0.000	2.054

a. Predictors: (Constant), Dummy_French, Age, Dummy_Italian
b. Predictors: (Constant), Dummy_French, Age, Dummy_Italian, Dummy_Pref, Dummy_Male
c. Dependent Variable: ATTITUDE

Source: Author’s work

Later, the analysis moved to the model’s assumptions checking, and witnessed acceptable VIF and tolerance values to reject potential multicollinearity issues (See Figure 28). Subsequently, homoscedasticity and linearity were tested and the absence of patterns in the scatterplot of residuals rejected any hypothesis of heteroscedasticity or non-linearity (See Figure 31).

Figure 31. *Residuals’ dispersion graph for the model adopted to test Hypothesis 2*



Source: Author’s work

Furthermore, the P- P Plot showed a good adherence of the points to the normal distribution curve, despite slight deviations.

- *Hypothesis 3:* Gender moderates the relationship between extraversion and students' attitude towards AI

No answers were obtained by extroverted individuals that selected the gender option *prefer not to say*. Hence, this hypothesis was only tested for the genders *female* and *male*.

For the test of *Hypothesis 3*, two interaction variables were created: *FemaleExt* and *MaleExt*. The regression was controlled for the variables *age* and *nationality*.

The *coefficients table* (See Figure 32) was firstly analyzed. The significance levels for the variables *FemaleExt* (p = 0.341) and *MaleExt* (p = 0.173) indicated that the model did not find significant relationships among the hypothesis' variables. Therefore, *Hypothesis 3* could not be accepted based on the results of this model.

Figure 32. *Coefficients of the regression ran to test Hypothesis 3*

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients			95,0% Confidence Interval for B		Collinearity Statistics	
		B	Std. Error	Beta	t	Sig.	Lower Bound	Upper Bound	Tolerance	VIF
1	(Constant)	5.065	0.528		9.598	0.000	4.019	6.111		
	Age	0.096	0.022	0.383	4.348	0.000	0.052	0.140	0.912	1.096
	Dummy_French	0.692	0.224	0.369	3.085	0.003	0.247	1.136	0.493	2.027
	Dummy_Italian	-0.091	0.182	-0.059	-0.503	0.616	-0.451	0.269	0.508	1.970
2	(Constant)	6.390	0.637		10.024	0.000	5.126	7.654		
	Age	0.075	0.021	0.297	3.566	0.001	0.033	0.116	0.865	1.157
	Dummy_French	0.588	0.212	0.314	2.776	0.007	0.168	1.008	0.469	2.132
	Dummy_Italian	-0.180	0.173	-0.117	-1.043	0.300	-0.524	0.163	0.475	2.106
	Dummy_Male	-0.420	0.428	-0.282	-0.983	0.328	-1.268	0.427	0.073	13.701
	Dummy_Female	-0.934	0.418	-0.635	-2.234	0.028	-1.763	-0.105	0.074	13.456
	FemalexExt	0.020	0.021	0.075	0.957	0.341	-0.021	0.062	0.987	1.013
	MaleExt	-0.045	0.033	-0.107	-1.372	0.173	-0.110	0.020	0.980	1.021

a. Dependent Variable: ATTITUDE

Source: Author's work

Later, assumption checks were run. No issues were found regarding normality, linearity or homoscedasticity, yet the VIF and Tolerance values for the two gender dummies showed potential multicollinearity. In light of the already stated impossibility to reject the null hypothesis, however, no further adjustments were made to the model.

- *Hypothesis 4*: Gender moderates the relationship between neuroticism and students' attitude towards AI

The same procedure adopted for *Hypothesis 3* was followed in this case, and two interaction variables were created- again, no answers were obtained by neurotic individuals that selected the gender option *prefer not to say*, consequently the analysis only focused on the male and female genders. *Age* and *nationality* were used as control variables in this model.

The coefficients table (Figure 33) was examined, revealing high significance levels for both of the two main independent variables of the model, respectively *FemaleNeu* (p = 0.680) and *MaleNeu* (p = 0.687). Assumption checks were performed and no specific validity issues were identified, except for high VIF and Tolerance values for the two gender dummies (Figure 33). Given the impossibility to reject the null hypothesis, no further manipulation was considered needed.

Figure 33. *Coefficients of the regression ran to test Hypothesis 4*

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	95,0% Confidence Interval for B Lower Bound	95,0% Confidence Interval for B Upper Bound	Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	(Constant)	5.065	0.528		9.598	0.000	4.019	6.111		
	Age	0.096	0.022	0.383	4.348	0.000	0.052	0.140	0.912	1.096
	Dummy_French	0.692	0.224	0.369	3.085	0.003	0.247	1.136	0.493	2.027
	Dummy_Italian	-0.091	0.182	-0.059	-0.503	0.616	-0.451	0.269	0.508	1.970
2	(Constant)	6.266	0.652		9.607	0.000	4.973	7.559		
	Age	0.080	0.022	0.319	3.702	0.000	0.037	0.123	0.829	1.206
	Dummy_French	0.585	0.217	0.312	2.694	0.008	0.154	1.016	0.456	2.191
	Dummy_Italian	-0.183	0.175	-0.119	-1.046	0.298	-0.531	0.164	0.473	2.113
	Dummy_Male	-0.447	0.433	-0.299	-1.031	0.305	-1.306	0.412	0.073	13.744
	Dummy_Female	-0.952	0.425	-0.647	-2.240	0.027	-1.795	-0.109	0.074	13.595
	FemaleNeu	0.008	0.019	0.036	0.414	0.680	-0.029	0.045	0.801	1.248
	MaleNeu	0.010	0.024	0.034	0.404	0.687	-0.038	0.057	0.888	1.127

a. Dependent Variable: ATTITUDE

Source: Author’s work

- *Hypothesis 5*: Nationality affects students’ attitude towards AI

For the test of this hypothesis, a One-Way ANOVA was run. The Levene test showed how the homogeneity of variances was respected in this model, as the p-value was found to be greater than 0.05 (p = 0.662). Moreover, the ANOVA table illustrated the presence of significant differences among the nationality groups’ means, in terms of attitude towards AI (F = 5.486; p = 0.005) (See Figure 34).

Figure 34. *Coefficients of the regression ran to test Hypothesis 5*

ANOVA

Attitude towards AI

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	5.002	2	2.501	5.486	0.005
Within Groups	50.602	111	0.456		
Total	55.604	113			

Source: Author’s work

Subsequently, post-hoc tests (Tukey HSD and Bonferroni) were run to understand the nature of the differences among groups (Figure 35). What was found is that Italian students have a more positive attitude towards AI with respect to French students, given the positive mean difference between these two groups (I-J = 0.56755). No significant differences were found for the other nationality students. In light of the obtained results, the *null hypothesis* was rejected.

Figure 35. *Tukey and Bonferroni tests table for Hypothesis 5*

Multiple Comparisons

Dependent Variable:

(I) Nationality			Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	Upper Bound
Tukey HSD	0	1	0.56755*	0.17211	0.004	0.1587	0.9764
		2	0.51989	0.23781	0.078	-0.0450	1.0848
	1	0	-0.56755*	0.17211	0.004	-0.9764	-0.1587
		2	-0.04766	0.19542	0.968	-0.5119	0.4166
	2	0	-0.51989	0.23781	0.078	-1.0848	0.0450
		1	0.04766	0.19542	0.968	-0.4166	0.5119
Bonferroni	0	1	0.56755*	0.17211	0.004	0.1492	0.9859
		2	0.51989	0.23781	0.093	-0.0582	1.0980
	1	0	-0.56755*	0.17211	0.004	-0.9859	-0.1492
		2	-0.04766	0.19542	1.000	-0.5227	0.4274
	2	0	-0.51989	0.23781	0.093	-1.0980	0.0582
		1	0.04766	0.19542	1.000	-0.4274	0.5227

*. The mean difference is significant at the 0.05 level.
0 = group representing French nationality
1 = group representing Italian nationality
2 = group representing other nationalities

Source: Author’s work

- *Hypothesis 6*: The place of residence affects students' attitude towards AI

The test of *Hypothesis 6* followed the same reasoning used for *Hypothesis 5*. The Levene test indicated that the assumption of homogeneity of variances was met ($p = 0.833$). The ANOVA showed a significance of $p = 0.011$, indicating that there are statistically significant differences among the groups. Consequently, the Tukey HSD and Bonferroni tests were performed to understand the nature of these differences (Figure 36). In this case, no statistically significant differences were found between the groups at the 0.05 significance level. Therefore, not enough evidence was collected to reject the null hypothesis. Yet, p-values close to the threshold of 0.05 suggest that there might be differences among the groups, which could potentially be identified by running the same test with a larger sample size.

Figure 36. *Tukey and Bonferroni tests table for Hypothesis 6*

Multiple Comparisons

Dependent Variable:

(I) Residence			Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	Upper Bound
Tukey HSD	0	1	0.371810401	0.15684	0.051	-0.0008	0.7444
		2	-0.38715	0.36692	0.544	-1.2588	0.4845
	1	0	-0.371810401	0.15684	0.051	-0.7444	0.0008
		2	-0.75896	0.34751	0.078	-1.5845	0.0666
	2	0	0.38715	0.36692	0.544	-0.4845	1.2588
		1	0.75896	0.34751	0.078	-0.0666	1.5845
Bonferroni	0	1	0.371810401	0.15684	0.058	-0.0094	0.7531
		2	-0.38715	0.36692	0.881	-1.2791	0.5048
	1	0	-0.371810401	0.15684	0.058	-0.7531	0.0094
		2	-0.75896	0.34751	0.093	-1.6037	0.0858
	2	0	0.38715	0.36692	0.881	-0.5048	1.2791
		1	0.75896	0.34751	0.093	-0.0858	1.6037

0 = group representing residence in France
1 = group representing residence in Italy
2 = group representing residence in other countries

Source: Author's work

- *Hypothesis 7*: Students who use AI tools more often within their academic journey are more satisfied of AI than those who use them more rarely
- *Hypothesis 8*: A positive attitude towards AI is associated with higher levels of satisfaction towards AI tools.
- *Hypothesis 9*: Concerns about AI use (e.g., ethical concerns, privacy issues) affect the relationship between positive attitude and satisfaction of AI in academic contexts

These latter hypotheses were tested using diverse models within the same regression. Respectively, *Hypothesis 7* = Model 2, *Hypothesis 8* = Model 3, *Hypothesis 9* = Model 4. *Gender*, *age* and *nationality* were used as control variables.

Firstly, the coefficients table was analyzed (See Figure 37). For Model 2, frequency of use was found to be significantly associated with the satisfaction levels (standardized $\beta = 0.241$, $p = 0.041$). Consequently, the null hypothesis for *Hypothesis 7* was rejected.

For Model 3, what was found is that attitude is associated with satisfaction levels (standardized $\beta = 0.271$, $p = 0.036$. The null hypothesis for *Hypothesis 8* was rejected.

Finally, Model 4 was observed and the correlation between the interaction variable *AttitudexConcerns* and *Satisfaction* was found to be significant ($p = 0.003$) and negative (-0.312). Also in this case, the null hypothesis for *Hypothesis 9* was rejected.

Model 3 was then used as a basis for the assumption checks. The VIF and tolerance values were observed, not finding multicollinearity issues (See Figure 38). The P-P Plot (Figure 39) and the scatterplot of residuals (Figure 40) did not show issues related to linearity, normality or heteroscedasticity, either. Consequently, the models' results were considered valid for the purposes of the study.

Figure 37. *Coefficients of the models used to test Hypotheses 7, 8 and 9*

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	4.080	1.326		3.077	0.003
	Age	0.110	0.058	0.205	1.907	0.060
	Dummy_Male	0.533	0.312	0.178	1.711	0.091
	Dummy_Pref	-0.274	0.971	-0.029	-0.282	0.779
	Dummy_French	0.616	0.381	0.174	1.616	0.110
	Dummy_Othernat	1.310	0.423	0.326	3.099	0.003
2	(Constant)	4.298	1.305		3.294	0.001
	Age	0.067	0.061	0.123	1.098	0.275
	Dummy_Male	0.380	0.314	0.127	1.208	0.231
	Dummy_Pref	-0.733	0.978	-0.076	-0.749	0.456
	Dummy_French	0.251	0.413	0.071	0.607	0.545
	Dummy_Othernat	1.166	0.420	0.290	2.774	0.007
	Frequency of use	0.294	0.141	0.241	2.078	0.041
3	(Constant)	1.537	1.820		0.844	0.401
	Age	0.036	0.061	0.067	0.592	0.555
	Dummy_Male	0.122	0.331	0.041	0.369	0.713
	Dummy_Pref	-1.027	0.968	-0.107	-1.061	0.292
	Dummy_French	0.009	0.420	0.003	0.021	0.983
	Dummy_Othernat	1.104	0.413	0.275	2.675	0.009
	Frequency of use	0.187	0.147	0.153	1.271	0.207
	Attitude	0.532	0.249	0.271	2.132	0.036
4	(Constant)	3.007	1.799		1.672	0.098
	Age	0.007	0.059	0.013	0.115	0.908
	Dummy_Male	0.046	0.316	0.016	0.147	0.884
	Dummy_Pref	-0.235	0.958	-0.024	-0.245	0.807
	Dummy_French	0.215	0.406	0.061	0.530	0.597
	Dummy_Othernat	1.072	0.393	0.267	2.726	0.008
	Frequency of use	0.125	0.142	0.103	0.883	0.380
	Attitude	0.494	0.238	0.251	2.073	0.041
	AttitudexConcerns	-0.123	0.040	-0.312	-3.071	0.003

Coefficients[a]

a. Dependent Variable: Satisfaction

Source: Author's work

Figure 38. *Close up of Model 3's coefficients, with collinearity statistics*

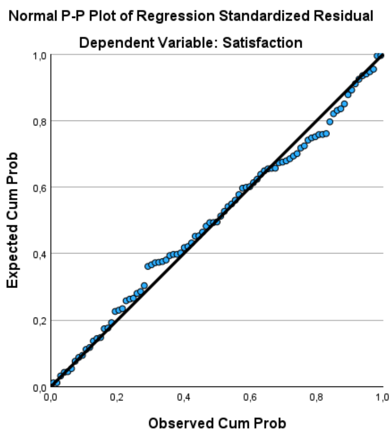
Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	VIF
3	(Constant)	1.537	1.820		0.844	0.401		
	Age	0.036	0.061	0.067	0.592	0.555	0.716	1.397
	Dummy_Male	0.122	0.331	0.041	0.369	0.713	0.750	1.334
	Dummy_Pref	-1.027	0.968	-0.107	-1.061	0.292	0.900	1.111
	Dummy_French	0.009	0.420	0.003	0.021	0.983	0.648	1.544
	Dummy_Othernat	1.104	0.413	0.275	2.675	0.009	0.869	1.151
	Frequency of use	0.187	0.147	0.153	1.271	0.207	0.629	1.590
	Attitude	0.532	0.249	0.271	2.132	0.036	0.568	1.760

Coefficients[a]

a. Dependent Variable: Satisfaction

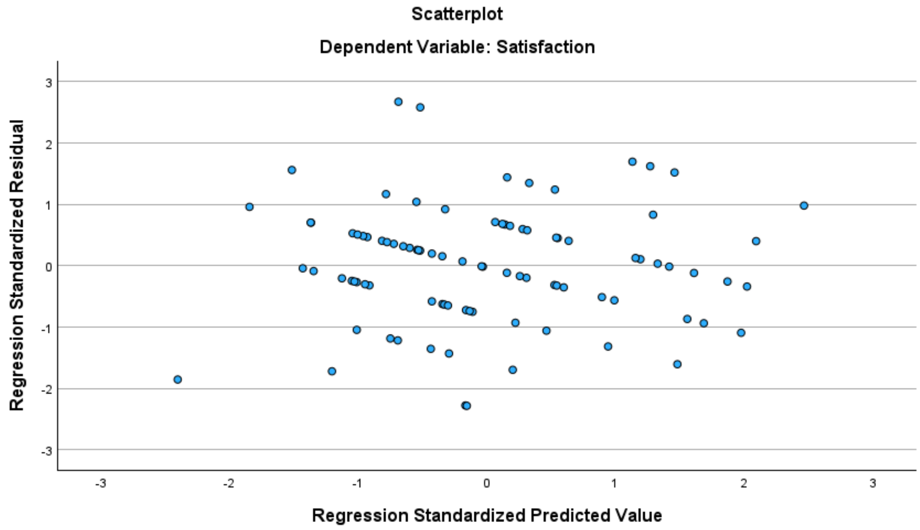
Source: Author's work

Figure 39. *P-P Plot for Model 3*



Source: Author's work

Figure 40. *Scatterplot of residuals for Model 3*



Source: Author's work

5.1.10 Survey results conclusions

Considerations were done after the review of the survey answers and the analysis of the 9 hypotheses of the study.

Figure 41 reports the results of the hypotheses tests, illustrating for which ones the null hypothesis was rejected, based on the significance and validity results.

Figure 41. *Summary of the Hypotheses for which the null hypothesis was rejected*

	Hypotheses for which the null hypothesis was rejected
HP 2	Gender influences students' attitude towards AI
HP 5	Nationality affects students' attitude towards AI
HP 7	Students who use AI tools more often within their academic journey are more satisfied of AI than those who use them more rarely
HP 8	A positive attitude towards AI is associated with higher levels of satisfaction towards AI tools
HP 9	Concerns about AI use (e.g. ethical concerns, privacy issues) affect the relationship between positive attitude and satisfaction of AI in academic contexts

Source: Author's work

In the following points are summarized the main findings of the quantitative part of the study:

- At the time of the survey, 80.7% of the sample had already used AI tools for academic purposes, at least once.
- In terms of frequency of use, most of the participants reported to use AI tools occasionally, often or very often. Moreover, the satisfaction levels were mostly concentrated between the scores 6,7 and 8 on a scale from 1 to 10, with 7 being the most selected option. A higher frequency of use of AI tools was found to be related to a more positive attitude towards AI.
- The most used AI tool among the sample units is ChatGPT, followed by Gemini and Microsoft Copilot. Participants also mentioned tools dedicated to more specific tasks, such as Llama and Mistral AI for text generation, Reverso for translation, Wisdolia and Consensus for text comprehension, DALL-E and Gamma for images and creative contents generation.
- The main uses that participants stated to do of AI tools in their academic journey are *research assistance, concepts clarification, summary and organization of large amounts of data, correction of grammatical errors and improvement of style in text inputs, exams preparation, problem solving, coding and programming assistance, creation of videos, images or presentations*.
- Among the survey units that never used AI tools before, the main reasons of no-use that were highlighted are represented by *the lack of necessity to use them, the personal preference to work without external aids, the personal will to only work with paper materials and books*, and *the scarce knowledge about the capabilities of these tools.*
- 39.82% of the participants affirmed to have concerns regarding the use of AI tools for academic purposes, these being mainly related to *the overreliance and dependency to the tools, reliability and accuracy of results, the lack of privacy and data security, the lack of interpersonal connection, the potential presence of biases, the fear of being penalized, the worry of a possible Internet addiction, the tools' costs and their general accessibility, the fear of job replacement, worries about a misuse of these tools for academic exams* and *the strong polluting effect of Artificial Intelligence servers' maintenance.* Moreover, the presence of concerns was found to moderate the relationship between positive attitude and satisfaction of AI in academic contexts.

- Insights were collected with regard to the influence of gender on attitude towards AI. In particular, male individuals and those students that chose the option *prefer not to say* were found to have a more positive attitude towards AI with respect to females. At the same time, no statistical evidence was found supporting the presence of an interaction effect between gender and personality on students' attitude towards AI.
- Nationality was found to have a certain effect on students' attitude towards AI, with Italian students having a more positive attitude with respect to French ones. Conversely, not enough statistical evidence was found to prove that the place of residence has an impact on students' attitude towards AI.
- A positive relationship between students' attitude towards AI and their satisfaction levels for these tools was detected.
- No relationship was found between students' field of study and their attitude towards AI tools.

5.2 Results of the Interviews

Interviews' outputs were found to be different, but characterized by similarities under various aspects. Recurring patterns were in fact found, as highlighted by the presence of very common codes within the interviews' content, like *ChatGPT*, *research*, *summarizing*, *over utilization* and *need for education*. Moreover, peculiar themes were delineated.
The final division of the interviewees was the following:

- four students of Università degli Studi di Perugia
- three students of LUISS University, in Rome
- three students of other Italian universities
- six students of ISG International Business School, in France

Interviewees' age ranged between 19 and 27 years old. Six of them identified as male, while the other ten identified as female. Regarding the students enrolled in Italian universities, all of them stated to be living in Italian cities, except for one, living in Montenegro. Additionally, eight of them declared to have Italian nationality, one to have Montenegrin nationality and one to have Ethiopian nationality. All of the students from ISG Paris Business school, instead, stated to be living in France and to have French nationality.
Nine out of the sixteen interviewees were attending an economics course, whereas each of the other participants was enrolled in a different degree program. Furthermore, the participants also varied in terms of their study level, with three interviewees attending a bachelor's

degree, five enrolled in a master's degree, seven attending a single-cycle master's degree and one enrolled in a PhD program.

5.2.1 Use of technology inside and outside university

Almost all of the interviewees stated to have a strong relationship with technology, reportedly using it during most of their daily lives, from the clock in the morning to social media scrolling in bed at night. Another aspect that was identified regards having different purposes for every tech tool used: participants indeed reported to use their smartphones mostly for leisure time and communication, whilst PCs and tablets are being used for working and studying for the bigger part.

When asked which tools they use the most in their academic path, interviewees gave a wide set of answers, ranging from the use of Google, to Microsoft Office programs, Canva and ChatGPT. In this context, it has been observed how two of the participants mentioned ChatGPT among the tech tools they use to study before being asked about their use of AI in particular, suggesting that this instrument is already well-established within their study method.

5.2.2 AI knowledge, familiarity and general use

Despite all of the participants stating to often use technology, the answers on their information level about AI revealed a more diverse scenario. In fact, four out of sixteen interviewees reported not to be enough informed about AI, five of them believe to be informed enough while the other seven stated to be very informed. However, all of the participants have used AI tools at least once, and only two of them are not familiar with their utilization. In terms of the types of instruments to be used, a pattern was found: every participant named ChatGPT first, when speaking of the AI tools they had used or were using at the moment of the interview. Only one of them also mentioned other language models as well, like Gemini, Mistral and LLaMA, while two participants named Python as one of the AI instruments they have been using, despite it not being properly an AI tool, but an instrument that can also facilitate the development of AI programs.

The areas in which interviewees have used AI only cover university and, in a few cases, the workplace. Many similarities were found in this sense as well, with participants reportedly using AI tools for research and summaries; few of them also stated to leverage AI for code generation, rephrasing, image creation and exams preparation. Only one of the participants stated to have knowledge of specific techniques to obtain effective answers.

5.2.3 Opinions and perceived benefits

Fourteen out of sixteen reported to have benefited from the use of AI within their academic path, especially in terms of time savings, even if with different frequencies of use. Two of them affirmed instead not to have positively leveraged AI, because of a personal choice not to use these tools often, preferring to just work with their own capacities.

Another interesting aspect that arose from the interviews' outcomes regards the answers to the following question:

What is your opinion with regard to these tools? Are you satisfied with them?

The satisfaction level was in fact found to be very diverse among the participants, and not related neither to the information that the sample units possessed about AI, nor to their general familiarity with AI. The positive traits that interviewees underlined about the use of these tools comprehend:

- their overall efficiency and the consequent better time management
- the state of mind improvement: specifically, one participant reported to have reduced her anxiety thanks to the introduction of AI in her study path
- the possibility to receive answers and explanations for mathematic queries and, more generally, the help for exams preparation
- the help in summarizing papers
- the ability to quickly create prompts and examples for formal written outputs, like emails

Despite delineating these beneficial aspects, five out of sixteen participants stated not to be fully satisfied with these tools because of certain negative drawbacks.

5.2.4 Concerns

Independently from the satisfaction level, a total of twelve out of sixteen participants affirmed to have concerns regarding their use. One of the other two interviewees was the PhD student: he reported that, although he was not personally worried, if he were born sooner he may have used it to simplify his studying habits, hence to be concerned about a potential misuse by younger generations.

Here are reported the concerns expressed by the participants of the interview about the use of AI in academic contexts:

- 10 out of 16 participants reported having concerns related to the tools' reliability, highlighting the possibility to receive wrong or inaccurate answers and the need to always double check the outputs.
  For this point in particular, One participant stated to have noticed how ChatGPT proposed her a wrong answer by making wrong deductions from the inputs received, another explained how the summaries he asked the chatbot to do were often missing important parts of the original text. Lastly, one interviewee also underlined the problems related to receiving outputs based on non-updated data.
- 9 out of 16 participants stated to be concerned about students' excessive facilitation of instruction path, especially for the youngest, that may lose their ability to think critically and their learning capacities. More generally, these sample units have expressed concerns about "lazy" students substituting themselves with AI, risking to obtain non-deserved results, reducing the validity of their academic accomplishments and damaging their creativity, effort and motivation.
  With this regard one of the participants, studying Education and Training, admitted to being afraid of having to deal with this type of scenario in her future profession as a teacher.
- 7 out of 16 participants stated to be worried about students' overdependence on these tools
- Two participants expressed concerns about the inability to control their level of plagiarism and the risk of being AI-detected.
  Specifically, one of them reported how she was once penalized for an assignment that was completely done by her, but was detected as AI-work by the university's checking tool. On the other hand, another participant expressed concerns regarding the possibility for students to modify works that are entirely AI-produced, escaping the detection tools
- Finally, one interviewee stated to be worried about the possibility of losing her future job as a translator, due to AI. Yet, she also underlined how these tools do not have the emotional capabilities of a human in comprehending language details.

5.2.5 Participants' suggestions on improvement and regulation

Eleven out of sixteen interviewees demonstrated to have a positive attitude towards AI tools' evolution in academic context, stating to see a potential in them. Three of them specifically expressed the belief that future evolutions will strongly reduce their errors and limitations, consequently lowering their reasons of concern. Here reported are two affirmations, by these participants, that can help better understand their position on this aspect:

- "I think those tools will be a new 'Google' in a couple of years."
- "… we need to understand that we don't need to boycott AI, but to use it as a strength for the future."
- "I believe ChatGPT to be a very useful tool, because it can help me in different situations. However, I am partially satisfied because answers are sometimes erroneous or incomplete, but I believe this is mostly due to the high specificity of the question. Anyway, this tool is rapidly evolving, so I believe that these issues will be less and less frequent in the future."

Furthermore, 4 of the participants expressed the need for education and information about AI tools, with the aim of allowing people to acknowledge their pros and cons, risks and potentialities. A non-critical use, in this sense, is depicted as damaging, especially for students and their ability to complete tasks by themselves.

Finally, all of the interviewees agreed on the need for regulations about the use of AI tools in universities. In particular, the most touched themes about regulations regard:

- the avoidance of a complete banning, that could deprive students of a powerful tool
- the need for a better control of the huge potential of AI tools
- different regulations on the basis of the educational level of the student
- the allowance of their use during study sessions, for research, questions, summaries and other activities, intertwined with the obtainment of rules able to refrain students from substituting themselves with AI in their educational paths and doing a "copy and paste" work
- the ban of AI tools during formal exams
- the improvement of detection tools, to avoid both false positives and false negatives cases

6. Discussion

This study had the purpose to analyze the role that university students have of Artificial Intelligence tools within their academic journey, and to investigate the factors potentially influencing their perception of these instruments. The mixed methodology approach favored the comprehension of a multifaceted context, also allowing comparisons between different countries and groups of students.

6.1 Role of AI Tools in Participants' Academic Path

For what regards the role that students give to AI tools in their academic journey, what was found is that most scholars, both from France and Italy, had already used these instruments at least once, at the time of the survey and interviews. The interviews revealed a peculiar pattern in terms of knowledge: despite almost all of the participants stating to have a good relationship with technology, and to be using AI tools (as reported by almost 81% of the survey participants), their information level regarding Artificial Intelligence was demonstrated to vary from student to student, with very few students retaining to be experts. This result was found to be coherent with those of similar studies on the topic (Idroes *et al.*, 2023).

Both the survey and the interviews' participants contributed to the delineation of the role and uses that students do of AI tools for university. What was found is that scholars mostly rely on Large Language Models, especially ChatGPT, which was mentioned by the 89.01% of the survey sample and all of the interviewees. Yet, other tools were listed as well, with participants stating to use them for more specific tasks (e.g.: Llama for text generation).

In general, students affirmed to use AI for a vast range of purposes, like research assistance, concepts clarification, problem solving, coding and programming assistance, creation of contents, summaries and exams preparation in general. Such findings were found to be aligned with the existing literature on the topic (Salas-Pilco & Yang, 2022; Stepanenko & Stupak, 2023; Chan & Hu, 2023; Balabdaoui *et al.*, 2024).

The scholars that stated not to use AI for academic purposes motivated this choice in different ways: the main reasons of no-use regard the lack of necessity to use them, a personal preference to work without external aids or to only study with paper materials, avoiding technology, and a sense of scarce knowledge about the capabilities of these tools.

The frequency of use of AI in academic contexts was found to be generally medium-high for most of the participants, both in the survey and the interviews.
No particular diversities were found between the Italian and French students in terms of the role they assigned to AI in their academic paths.

6.2 Students' Perception and Opinions on AI Tools

During the interviews, 87.5% of the participants reportedly benefited from the use of AI tools for academic purposes, especially in terms of time savings. The rest of the interviewees stated not to have benefited from these instruments because they preferred not to use them often, choosing to just work with their own capacities. Moreover, 73.33% of the interviewees affirmed to be overall satisfied with AI tools, highlighting positive traits such as better time management, help during study and exams preparation, and improvement of the state of mind.
Despite these mostly positive feedbacks, 39.82% of the survey sample and 75% of the interviewees affirmed to have concerns regarding the use of AI tools for academic purposes. Among the most mentioned sources of worry, the participants stated to have concerns related to the tools' reliability, the potential overdependence and the risk for students to substitute themselves with AI, obtaining underserved results and not achieving a proper level of formation. Potential risks for data security were also mentioned by 17.54% of the sample. Another interesting outcome regards the participants' fear of being penalized for the use of AI. One of the participants also shed a light on the fear of losing her job to AI. Again, these findings were found to be coherent with the existing literature (Chan & Hu, 2023; Von Garrel & Mayer, 2023; Güner *et al.*, 2024; Cotton, Cotton & Shipway, 2024).
However, most of the interviewees demonstrated a positive attitude towards AI's evolution in academic contexts, envisioning an evolution able to strongly reduce their errors and limitations, and consequently reducing their reasons of concern. The quantitative analysis of the survey results was pivotal in this part of the study, finding how students' attitude towards AI is related to specific factors, both demographic and personal. Specifically:

- A more positive relation was found between individuals identifying with the male gender with respect to females, in terms of attitude towards AI tools. This result is consistent with similar studies, which indicate that females tend to be more skeptical than males about the use of AI tools (Balabdaoui *et al.*, 2024). Yet, no cross-relationship was identified between gender, personality and attitude, which is contrary to the expectations based on existing literature (Hamburger & Ben-Artzi, 2000; Park & Woo, 2022). However, considerations were made on the fact that these studies differ in their sample population and investigated variables, which may explain the different results.

- A higher frequency of use of AI tools was found to be related to a more positive attitude towards AI.
- Attitude was found to positively influence students' satisfaction levels towards AI tools.
- An influence was discovered between students' concerns on AI tools and their satisfaction levels. Specifically, the presence of concerns reduces the effect of attitude on the satisfaction levels of the students.
- A positive relationship was found between students' nationality and their attitude towards AI, for what regards the Italian students in particular. This result is partly those of Guhr *et al.*'s study (2003), which found nationality and technology readiness to be somehow related, even if also influenced by the presence of additional factors. Again, the presence of different variables cannot allow a perfect comparison between these studies.
- No relationship was found between students' field of study and their attitude towards AI, hence not supporting the findings of existing literature with this regard (Balabdaoui *et al.*, 2024).
- No relationship was found between students' place of residence and their attitude towards AI.

Additionally, the interviews made it possible to investigate participants' ideas and suggestions with regard to the regulations of the use of AI tools. In this context, their ideas were found to be similar on a certain level: the general topics that emerged from this question regarded the need for a double-sided approach, based on regulatory improvements and education on the use of these instruments. All of the interviewees agreed on not banning AI tools for students, but clearly determining the areas in which their use is acceptable and to which extent.

Finally, participants highlighted the need for more advanced detection tools, able to reduce the rate of false positives and false negatives.

7. Limitations and Future Directions

Despite the valuable insights offered by this study, some limitations are present and need to be acknowledged for a more complete understanding and evaluation of the outcomes.

7.1 Sample Selection and Convenience Sampling

As already described within the previous sections, the experimental part of this study was developed by the means of a survey and a set of interviews. Both the individuals that participated in the interviews, and the units that executed the questionnaire, were not randomly chosen, due to the impossibility to contact and ensure the participation of randomly selected students; hence a convenience sampling was implemented.

In light of this, the research has a non-probability sample, limiting the generalizability of the results. Such phenomenon entails a reduced representativeness with respect to probability samples: in this case, for instance, a disproportion was found in terms of university of belonging and gender. In fact, both for the survey and the interviews, a main predominance of sample units enrolled in Italian universities was found, as well as a majority of women respondents. Specifically, finding participants enrolled in French universities was slightly difficult for the researcher, due to the low response rate and low connections. Moreover, in the case of the survey only, a disbalance in the distribution of the participants' field of study was found as well, with a majority of students enrolled in courses related to economics. These are some frequent consequences of the convenience sampling methodology, yet they do not damage the explorative scope of the study. Further research may consider recreating this analysis on a probability sample, for more generalizable results.

7.2 Self-Selection Bias

The students that received the questionnaire had the possibility to autonomously decide whether to complete the survey or not. Consequently, self-selection bias results to be another limitation of this study, potentially skewing the sample's answers towards the opinion of those who effectively completed the survey. Specifically, being the survey conveyed through an online platform, it is possible that those who completed it were predominantly tech-savvy individuals (Idroes *et al.*, 2023).

This latter limitation can be found in the interviews as well, since all of the consulted units were contacted via email or social media and they had the opportunity to choose whether to participate or not.
Further research on the topic might extend this study to a more representative sample, with the aim of obtaining more generalizable results.

7.3 Social Desirability Answer Bias

The responses' anonymity was explicitly guaranteed at the beginning of the questionnaire and in the preliminary phase of the interviews, with the aim of reducing the impact of the social desirability bias on the quality of the answers in terms of honesty and accuracy.
However, such distortion may still have had an impact on the sample's answers and the consequent results of the study.

7.4 Fatigue

The survey was crafted in a way to be as short as possible, yet the need to collect much information and use specific scales inevitably made it slightly heavy. This characteristic was probably noticed by the participants, who in some cases did not complete the questionnaire. The main consequence of this limitation is a lack of complete information, since several responses were interrupted before answering all of the questions. A suggestion for future research may be to create a shorter survey, by excluding some variables from the analysis.

7.5 Common Method Bias

Common method bias was tested following the Harman's Test (Podsakoff et al., 2003). However, even if the test that was run did not show the presence of substantial common method bias, further research may consider running additional analyses as well.

7.6 Survey Scales' Translation, Structure and Results

Another potential limitation of the study can be found in the personality and attitude scale used in the survey- respectively, the Eysenck and GAAIS scale.
Firstly, these scales were translated in Italian and French by the researcher: despite paying attention to the preservation of the meaning of the affirmations, it cannot be excluded that slight nuances of language may have got lost in translation.

Moreover, for the personality test in the survey, a decision was taken to rely on the previous research of Hamburger and Ben-Artzi (2000), hence using a set of questions aimed to only test the extraversion or neuroticism of participants, and to insert in the survey the short version of the scale (Eysenck, 1958), to limit the fatigue of participants and reduce the survey dropout rate. A suggestion for further research is to analyze the potential effects of other personality traits on students' relationship and attitude towards AI, or to recreate the same study with the full version of the original scale, to investigate potential changes in the results.
Finally, another important aspect to be considered regards the analysis of the results obtained with the attitude scale: authors did not give peculiar suggestions on how to work with the outputs, which necessitated some manipulation to make them ready to be analyzed in SPSS. However, the additional work done on data may have introduced slight alterations that may have influenced the interpretation of the findings.

7.7 Assumptions Checks

Most of the regressions run to test the hypotheses of the study provided significant results, yet did not pass the assumption checks for multicollinearity, linearity, normality and homoscedasticity. This aspect needs to be carefully considered when analyzing the study's quantitative results. A suggestion for further research could be to test the hypotheses again, with different models.

7.8 Time Limitations

The design that was given to this research determined that the experimental data of the study was collected in one single time frame. Consequently, the results may not account for potential changes in students' perception and attitude of AI over time.
In light of this, future research may extend the analysis on different time periods, to investigate a broader set of results and potentially gain new insights on the study's topic.

7.9 Other External Factors' Influence

Various further factors that have not been analyzed in this research may have influenced the quality of the outcomes.
An important aspect, potentially influencing the survey's results, regards the sample units' ease of use of technology. A student that believes to have a high competence with

technological devices in general, or possessing additional assistance in the use of the tools, may give responses that are not completely objective regarding their relationship with AI, expressing a perception that is more positive than others because of these factors.

Similarly, the voluntariness of use, the perceived complexity of use and the perceived individual relevance of technology may affect the perception of AI (Gado *et al.*, 2022).

A suggestion for further research may involve the creation of a similar study comprehensive of these considerations, to analyze whether these factors actually have an effect on the relationship among the measured variables.

Conclusions

This study finds place in the existing literature by conducting an explorative research on the role and perception of Artificial Intelligence in academic contexts, with a specific focus on the Italian and French environments. The method used for the investigation of the topic, and to answer the two research questions, consisted of a mixed methodology approach, aimed at reaching an holistic comprehension of the subject.

The obtained results described a peculiar framework. Students were found to assign important roles to AI, as an aid for studying, and expressed an overall good level of satisfaction towards these tools. Yet, most of the participants also affirmed to have concerns, especially in terms of reliability and over dependence, and emphasized the need to improve the students' education on these topics, as well as the necessity for updated regulations, able to set the boundaries for a smart use of AI in academic contexts.

Moreover, the results showed the presence of relationships between gender, nationality, frequency of use and the attitude towards AI tools. Additionally, the same attitude was found to be influential on students' satisfaction levels, showing some patterns regarding these specific characteristics and their perception of these tools.

Regarding the role, benefits and risks that students assigned to AI, no significant differences were found between the Italian and French samples. The participants demonstrated a similar level of knowledge and held comparable positive and negative opinions on these tools. Still, a more positive attitude to AI was observed among students of Italian nationality.

However, not all of the hypotheses of the study were confirmed. At the same time, it has to be taken into account how this study inserts in a gap of the literature, presenting a methodological approach that has not been explored yet for similar cases, consequently limiting the ability to compare results and validate findings against established benchmarks. Future research may build on these outcomes to expand the knowledge on this topic, also considering different samples.

As thoroughly analyzed along this research, Artificial Intelligence brought many changes to people's routines, with specific benefits and risks also in the educational field. The exponential use of these tools increased in recent years, and often did not find everyone ready for a smart and conscious use.

For this reason, the feedback received from the participants can serve as a strong starting point for improvements in regulations and education around these topics. Universities and policymakers could use this research as a foundation for practical actions, with the goal of informing, educating and regulating the impact of AI tools on students' academic routines.

List of Tables and Figures

Figure 39. P-P Plot for Model 3 (Author's work)

Figure 40. Scatterplot of residuals for Model 3 (Author's work)

Figure 41. Summary of the Hypotheses for which the null hypothesis was rejected (Author's work)

Glossary

Acquiescence bias	Bias based on participants' tendency to consistently agree with survey items, regardless of item content (Kam & Meyer, 2015)
AI	Artificial Intelligence
AI-giarism	Unethical practice of using artificial intelligence technology, particularly generative language models, to generate content that is plagiarized either from original human-authored work or directly from AI-generated content, without appropriate acknowledgement of the original sources or AI's contribution (Chan, 2023)
Artificial Intelligence Act	European regulation on artificial intelligence (AI), that lays the foundations for the regulation of AI in the EU (Future of Life Institute)
Attention check item	Specific item inserted in experiments, to check that participants are not being disattentive, and are providing thoughtful answers
Automation bias	Individuals' overreliance on algorithmic advice even in the face of "warning signals" from other sources (Alon-Barkat & Busuioc, 2023)
Bias	Problem related to the gathering or processing of data that might result in prejudiced decisions on the bases of demographic features such as race and sex (Ntoutsi et al., 2020)
Big Five personality traits	Widely accepted and comprehensive framework in the psychological field, classifying human personality on the basis of five dimensions: openness to experience,

	conscientiousness, extraversion, agreeableness and neuroticism (Park & Woo, 2022)
ChatGPT	Advanced language model based on the Generative Pre-trained Transformer architecture, able to generate coherent and contextually appropriate responses that closely mimic human-like communication (Chan & Zhou, 2023)
Common method bias	Systematic error in research studies, characterized by a response variance that is attributable to the measurement method (Aguirre-Urreta & Hu, 2019)
Computer Based Training	Programs designed for instruction or education, that provide content for the learners to be accessed through computers or other digital devices
Convenience sampling	Non-probability sampling method where participants are selected by the researcher, based on their accessibility and willingness to participate (Stratton, 2021)
Deep Learning	Subset of machine learning and designed to mimic the network of neurons in a brain (Ergen, 2019)
GAAIS	General Attitudes towards Artificial Intelligence Scale, designed by Schepman and Rodway (Schepman & Rodway, 2023)
General Data Protection Regulation	Data protection law in the European Union, directed at enhancing and unifying data protection rules within the member states and also aimed at ensuring a better control over individuals' personal data
Generative AI	Group of machine learning algorithms designed to generate new data samples that mimic existing datasets (Chan & Hu, 2023)

Intelligent tutoring systems	Computer-based educational tools, able to perform a wide range of functions, including grading and providing students with feedback on their work, by using AI (Chen *et al.*, 2020)
Knowledge Workers	Those who typically work at a desk (whether in an office or at home). This group includes those who are in person or working remotely in some capacity (Microsoft, 2024)
Large Language Models (LLMs)	Artificial Intelligence systems designed to understand and generate human-like text outputs, creating new content including text, imagery, audio, code, and videos in response to textual instructions (Harrer, 2023)
Machine Learning	Subset of artificial intelligence characterized by statistical instruments that are used to find patterns in massive amounts of data, which are then used to make predictions (Ergen, 2019)
Natural Language Processing	Interdisciplinary field leveraging artificial intelligence, linguistics and computer science to produce outputs in human languages (Ciesla, 2024)
Non-probability sample	Sampling method, less objective than probability techniques, in which the researcher uses sampling that does not provide for each member of a target population to participate in a study and rather the participants are selected by the researcher, are referred to the researcher, or self-select to participate in a study (Stratton, 2021)
Qualtrics	Web-based platform for the creation and distribution of surveys
Selective adherence	Selective adoption of algorithmic advice when this corresponds to stereotypes (Alon-Barkat & Busuioc, 2023)
Self Selection Bias	Bias caused by individuals self-selecting themselves into a

	group in an experiment, possibly causing results not to be representative of the whole population
Snowballing Method	Non-probabilistic sampling method, based on the possibility for sample units to recruit other sample units among their acquaintances or social networks
Social Desirability Bias	Bias related to the tendency of individuals to consciously or unconsciously falsificate answers in order to avoid rejection, criticism or social sanctions (Von Garrel & Mayer, 2023)
SPSS	Statistical Package for the Social Sciences. Software used for statistical analyses
Target Audience	Group of people identified as the target of a certain message or service and sharing characteristics such as demographics, interests, or behaviors. In this research's case, the term refers to the population of the study.

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