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The impact of Artificial Intelligence in education from teachers' perspective: a case study for primary and secondary schools

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October 2022

BUSINESS
SCHOOL

Department of Marketing, Operations, and General Management

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Acknowledgments

For the teachers who inspire so much and are inspired by their students,
For the parents who contribute so much to their kids' education,
For our inner kid, who still has so many questions about the world,
And for all the others.

Thank you.
I hope this thesis can be helpful to any curious grown-up kid out there.

Abstract

The rapid development of disruptive technologies such as Artificial Intelligence (AI) is offering exciting opportunities for the field of education. Under the premise that AI can help bridge gaps in learning and teaching and create new opportunities for schools, a growing number of practitioners and researchers have sought to understand the potential of these technologies in educational settings. But these innovations also come at a price, and it is critical to investigate whether the benefits of AI in education (AIEd) effectively outweigh its risks. In this regard, this study aims to analyze the impact of Artificial Intelligence in education, identifying the factors that contribute to the possibility of implementing AI in Portuguese primary and secondary schools. Using a mixed research approach and collecting data from a survey answered by 184 Portuguese teachers, this research tested the effects of three factors in particular: respondents' (1) knowledge and perceptions about the (2) benefits and (3) barriers of AI in education. The results indicated that the perceived benefits of AI in education strongly affect the intention to implement these technologies in the classroom, as opposed to the barriers. Also, knowledge of AIEd proved to be a significant factor, although teachers were more familiar with the potential of AI in theory than in practice. This situation, however, does not seem to compromise the intention to implement AI in Portuguese schools – on the contrary, it is reflected in a tendentially positive attitude towards this phenomenon.

Keywords: Artificial intelligence, AIED, Education, Teachers, K-12, Portuguese Schools

JEL Classification:
I21 Analysis of Education
O32 Management of Technological Innovation and R&D

Resumo

O rápido desenvolvimento de tecnologias disruptivas como a Inteligência Artificial (IA) está a trazer oportunidades empolgantes para o campo da educação. Sob a premissa de que a IA pode ajudar a colmatar lacunas na aprendizagem e no ensino e criar novas oportunidades para as escolas, um número crescente de profissionais e investigadores tem procurado compreender o potencial destas tecnologias em contextos educativos. Mas estas inovações vêm também com um preço associado, sendo por isso fundamental investigar se os benefícios da IA na educação (IAEd) compensam efetivamente os seus riscos. Neste sentido, o objetivo deste estudo é analisar o impacto da Inteligência Artificial na educação, identificando os fatores que contribuem para a possibilidade de implementar a IA nas escolas primárias e secundárias portuguesas. Utilizando uma abordagem de investigação mista e recolhendo dados de um inquérito respondido por 184 professores portugueses, esta investigação testou os efeitos de três fatores em particular: (1) os conhecimentos e as perceções dos inquiridos relativamente aos (2) benefícios e (3) às barreiras da IA na educação. Os resultados indicaram que os benefícios percebidos sobre a IAEd impactam significativamente a vontade de implementar estas tecnologias em sala de aula, ao contrário das barreiras. Também o conhecimento sobre AIEd demonstrou ter influência, apesar dos professores estarem mais familiarizados com o potencial da IA na teoria do que na prática. Esta situação, contudo, não parece comprometer a intenção de implementar a IA nas escolas portuguesas – pelo contrário, reflete-se numa atitude tendencialmente positiva em relação a este fenómeno.

Palavras-chave: Inteligência artificial, AIED, Educação, Professores, K-12, Escolas Portuguesas

Classificação JEL:
I21 Analysis of Education
O32 Management of Technological Innovation and R&D

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Glossary of Acronyms

AI – Artificial Intelligence

AIEd – Artificial Intelligence in Education

AGI – Artificial General Intelligence

ANI – Artificial Narrow Intelligence

ANNs – Artificial Neural Networks

ASI – Artificial Super Intelligence

CAGR – Compound Annual Growth Rate

EMT – Expectation and Misconceptions Tailored

GOFAI – Good Old-Fashioned AI

ICT – Information and Communications Technologies

IoT – Internet of Things

K–12 – Expression that covers all years from primary to secondary education (1^{st} to 12^{th})

KBS – Knowledge-based systems

KBS – Knowledge-based Systems

ML – Machine Learning

MOOC – Massive Open Online Course

PLS-SEM – Partial least squares structural equation modeling

SRL – Self-regulated learning

VUCA – Volatile, uncertain, complex, and ambiguous

Chapter I – Introduction

1.1. Framework and research problem

The transformations that have occurred in society in recent decades have challenged and changed the foundations that have formed the basis of progress over the past two centuries. Faced with increasingly complex problems and new paradigms, the field of education has been continually challenged to reformulate its assumptions and incorporate innovative practices designed for today's VUCA world – volatile, uncertain, complex, and ambiguous (Fadel et al., 2015; Flogie & Aberšek 2019; Millar et al., 2018). Against this unprecedented backdrop, an emerging set of technologies, widely known as Artificial Intelligence (AI), has been highlighted for their potential to address some of the most pressing problems across several domains such as agriculture, health, or education (Miao et. al, 2021).

Theoretically known as technologies that mimic human intelligence, the great promise of AI lies in its capability to interpret large amounts of data independently and autonomously adapt to achieve specific goals. From the most common applications, such as cookies in web browsers, to voice assistants in smartphones or self-driving cars, AI has been prevalent in several aspects of our lives (Haenlein & Kaplan, 2019; Ingkavara et al., 2022). For educational purposes, these technologies are contributing to the development of predictive and self-regulated learning (SRL), for example, by creating autonomous and customizable learning paths for leaners, or by supporting teachers through learning analytics (LA) to better understand their students' needs and aptitudes (Ingkavara et al., 2022; Mertala et al., 2022).

Despite the potential, the interdisciplinarity and complexity of the field of AI in education have resulted in many, often conflicting, views regarding the benefits and barriers that these technologies may entail in the sector. According to Howard et al. (2022), some challenges are still holding a mass spread of AI in European national educational systems: whether due to ethical reasons, lack of agreement and policy guidelines, or potentially conflicting views and understandings of the uses of data, several points are still being investigated to understand whether AI can meet its ultimate goal of widen quality education opportunities to a larger number of students rather than jeopardize children's very safe.

For this reason, it is important to understand the expectations, perceptions, and attitudes towards the use of AI in school contexts. In particular, this research focuses on the factors that influence teachers' willingness, as they are the ultimate agent responsible for a successful integration of AI in schools. As Mertala et al. (2022) state, research on people's conceptions and attitudes toward AIEd is still at an early stage, especially with regard to teachers (Ayanwale et al., 2022).

To bridge this gap with knowledge, this study proposes a mixed methodology supported by a questionnaire in which 184 Portuguese teachers from primary and secondary schools participated. The first analysis uses descriptive and analytical statistics to analyze whether socio-demographic variables influence the respondents' knowledge of AIEd. Factors such as gender, level of education, area of education, or age are explored. Once framed the first hypothesis, partial least squares structural equation modelling (SEM-PLS) will be used to understand possible relationships between the main variables of this study (perceptions about the barriers, the benefits, and knowledge of AIEd) and their impacts on their intention to implement these systems in classroom settings. Finally, a qualitative sentiment analysis will be conducted to understand better the relationship between sentiments and behavioral intention to implement AI in schools.

1.2. Research Objective

The present dissertation is guided by the main goal of understanding the impact of AI in education from two perspectives: one theoretical and one empirical. Under the theoretical side, this thesis seeks to contribute to the research field of AI in Education (AIEd) by adding knowledge regarding the impact of these technologies and the main factors that, according to a group of Portuguese teachers, seem to influence their implementation in primary and secondary schools. Hopefully, these findings could serve researchers to advance or integrate the existing model.

Empirically speaking, this thesis aims to promote an evidence-based and meaningful use of AI in educational settings, helping educational and non-educational agents, including companies and educational decision-makers, to make thoughtful and sustained decisions in designing technological solutions for the education sector. Taking a comprehensive approach, this dissertation also highlights the role of educational technology (EdTech) companies, considering industry-specific factors in the conceptual model and assessing whether they could affect, from the teachers' point of view, the successful integration of AI in Portuguese 1st to 12th grade (K-12) schools.

Regarding the specific research question that has guided this study, it is: *What is the possibility of implementing AI in Portuguese primary and secondary schools?*

1.3. Thesis Structure

This study follows the scientific process and is organized as follows:

In Chapter II, a literature review is conducted and divided into two moments: first, a set of theoretical views about AI are reviewed, including the concept of AI, historical contextualization, AI technologies, subfields and techniques, and practical implementations. Then, scientific evidence on the implementation of AI technologies in education is gathered around the *why*, *how*, and *what* are the requirements for applying these technologies to support teaching and learning.

Following the literature review, Chapter III presents the theoretical approach, research objective, question, and hypotheses. Chapter IV presents the methodology adopted in the study, followed by the analysis of data gathered and critical discussion in chapters V and VI. Finally, Chapter VII provides the main conclusions and implications, followed by recommendations for future research on this topic.

Chapter II – Artificial Intelligence

Throughout the history of humankind, a hidden desire to understand and simulate nature, and particularly the human being itself, has punctuated a wide range of technological manifestations. Looking two thousand years backwards, the general idea of a human-built 'artificial' intelligence or living being could already be seen in the temples of ancient Egyptian societies, hidden in mechanisms that created the illusion of speaking statues, removable parts, or opening doors (Dautenhahn, 2007). Since then, many other transformative technological revolutions have dramatically changed the way we live and operate within our societies: from the invention of the wheel to printing and electricity (Neves & Holmes, 2020). But only recently, with the emergence of a disruptive set of technologies broadly known as Artificial Intelligence (AI), humans became closer to mimicking what makes us more human — our intelligence.

Over the course of the last decade, and in particular in recent years due to some prominent successes and disruptive potential, applications of AI to improve and automate human activities have grown at an exponential rate. According to Bogoviz et al. (2019), AI has become so pervasive these days that it has been considered the most promising digital technological force of the fourth industrial revolution (Bogoviz et al., 2019; Holmes et al., 2019). In line with Gartner's (2021) *Hype Cycle for Emerging Technologies*, AI will continue to play a key role in enabling industry growth and innovation — and the enterprises that can establish best practices for emergent AI techniques will generate three times more value than the enterprises that do not. But despite being pervasive in so many aspects of our lives, why does our perception of Artificial Intelligence remain so nebulous (Atkinson, 2016)?

2.1. Understanding AI: Concept and definitions

A long-running debate among the scientific community to establish a commonly agreed-upon definition of "Artificial Intelligence" has prevailed since the field's very beginnings. Throughout its sixty-five years of existence, various theoretical understandings of AI have multiplied, intertwined with questions about the essence and reproducibility of *intelligence* itself (Miao et. al, 2021). Quoting Sternberg, R. J. (Gregory,1998), "viewed narrowly, there seem to be almost as many definitions of intelligence as there were experts asked to define it." In an interview with Brockman (1998), Marvin Minsky — one of the founding fathers of AI — justified that this issue is rooted in the fact that 'intelligence' is a suitcase word[1] that encompasses a bunch of different meanings, making it a real challenge when trying to apply such a fuzzy idea to machines (Kaplan & Haenlein, 2019).

[1] Suitcase words are terms that carry a range of different meanings that come along to our minds and can lead to misinterpretation (ex: 'learning', 'intelligence' or 'consciousness') (Brockman & Minsky, 1988).

For the sake of clarity, and taking a broader perspective, it can be said that the concept of Artificial Intelligence (AI) lies on the premise that machines can operate tasks that underlie thought processes and intelligent behavior (Atkinson, 2016; Cunha, 2021). According to Haenlein & Kaplan (2019), for a system to be considered *intelligent*, it must be able to interpret large amounts of external data independently and flexibly adapt to meet the specific outcomes. Along the same line, da Costa et al. (2020) define AI as a set of methods, tools, and systems for solving problems that typically require the use of human intelligence.

2.2. The evolution of AI

Before AI was formally introduced as a scientific discipline, the idea of creating intelligent machines was already taking root. Studies by Haenlein & Kaplan (2019) and Russell & Norvig (2021) state that the starting point for the discussion on Artificial Intelligence dates back to the 1940s, with the science fiction short story 'Runaround' written by Isaac Asimov. In a different view, Couceiro et al. (2020) define the very beginning of modern studies of AI in 1943, when Warren McCulloch and Walter Pitts developed the first artificial neural network model — a model that worked with an 'on' or 'off' state that varied according to the response to a stimulus received by the artificial neurons (Emmert-Streib et al., 2020). Anyway, of the early studies that anticipated the emergence of AI, an apparent consensus seems to reside among academics regarding Alan Turing's famous seminal article *Computing Machinery and Intelligence* (1950), whose fundamental work defined artificial intelligence (Couceiro et al., 2020; Russell & Norvig, 2021). Popenici & Kerr (2017) state that this study featured an essential step to the question of whether machines designed by humans could be considered intelligent. Briefly, "The Turing Test" (or "The Imitation Game") was designed as an experiment to evaluate whether a human interrogator, after posing some written questions, could understand if the responses come from a human or a computer. If not, the computer passed the test and would be considered "intelligent" (Russell & Norvig, 2021).

A few years later, in the two-month workshop at Dartmouth College (1956), the word 'Artificial Intelligence' was officially coined, along with its very first definition — "the science and engineering of making intelligent machines" (McCarthy, 1985; Pan, 2016). This famous workshop, later considered the beginning of the AI Spring (and AI's history), reunited the *founding fathers* of AI, a group of scientists who set forth the directions for the brand-new field (Haenlein & Kaplan, 2019). Over the following decades, the research field has developed in fits and starts, with periods of exciting advances intercepted by periods of stagnation (the two well-documented AI Winters[2]), marked by general disbelief and decreased research and development funding for AI (Haenlein & Kaplan, 2019; Holmes et al., 2019; Perrotta & Selwyn, 2020; Miao et. al, 2021).

[2] The two AI Winters covered the period between 1974–80 and 1987–1993, respectively (Lim, 2018).

According to Dwivedi et al. (2021), from the Dartmouth Conference onwards, the history of Artificial Intelligence has unfolded into three evolutionary stages triggered by specific AI subfields: (1) the expert systems era, (2) the knowledge-systems era, (3) and the last one that combines Machine Learning and Data Mining. This last stage, also known as *the implementation era*, is where we are currently situated (Neves & Holmes, 2020). Briefly, and in line with Duan et al. (2019), expert systems were prevalent from the birth of the field of AI until the beginning of the 21st century (although they are still common nowadays). Also known as 'classical AI', 'symbolic AI', 'rule-based AI', or 'Good Old-Fashioned AI' (GOFAI), these systems receive information from human domain experts and are programmed to reproduce their processes through procedural logic methods (if/then) to perform specific tasks (Perrotta & Selwyn, 2020; Miao et. al, 2021). For this reason, expert systems are particularly efficient when applied to areas requiring rule-based expertise formalization. In turn, the same cannot be said about mimicking human reasoning or learning, in which if/then statements still lag far behind (Duan et al., 2019; Miao et. al, 2021). This limitation was at the root of both winters of AI, as expert systems cannot achieve the ultimate goal of reaching human intelligence (Lim, 2018).

Following Dwivedi et al. (2021), knowledge-based systems (KBS) emerged virtually simultaneously with the expert systems era. Briefly, these systems are similar to the ones above in that they both contain a knowledge base provided by an expert in the field. However, knowledge-based systems support an inference engine, which allows knowledge to be deduced from the information covered in the knowledge base (Akerkar & Saija, 2009; Dwivedi et al., 2021).

The turning point of AI came mainly with the emergence of subfields such as Machine Learning, Deep Learning, or Data Mining. Chaves, A. (2021) highlights a particular event that changed the course of the history of AI: when IBM's intelligent chess-playing system *Deep Blue* defeated the world chess champion Garry Kasparov, in 1997. That moment captured the realization that computers could perform tasks previously considered unique to humans and were finally closer to reaching intelligence.

Since then, AI has developed at an unprecedented level, with a mass deployment of real applications based on these emergent paradigms. The reason behind the success of the *implementation era* can be primarily attributed to a shift of paradigm: from abstract formal logic principles (symbolic) to methods of statistical inference, along with a change from inductive to abductive reasoning (Perrotta & Selwyn, 2020). Some studies highlight that this paradigm shift would never be possible without recent technological advancements. To name a few, increased computer processor power, greater data storage capacity, highly capable central processing units, unleashed cloud computing and the latest advances in Big Data, 5G, and Internet of Things (IoT) have enabled tremendous advances in the field (Bozkurt et al., 2021; Haenlein & Kaplan, 2019; OECD, 2018). In addition, the hype around AI and increasing demands from industries have also been reflected in heavier funding for R&D (Bozkurt et al., 2021).

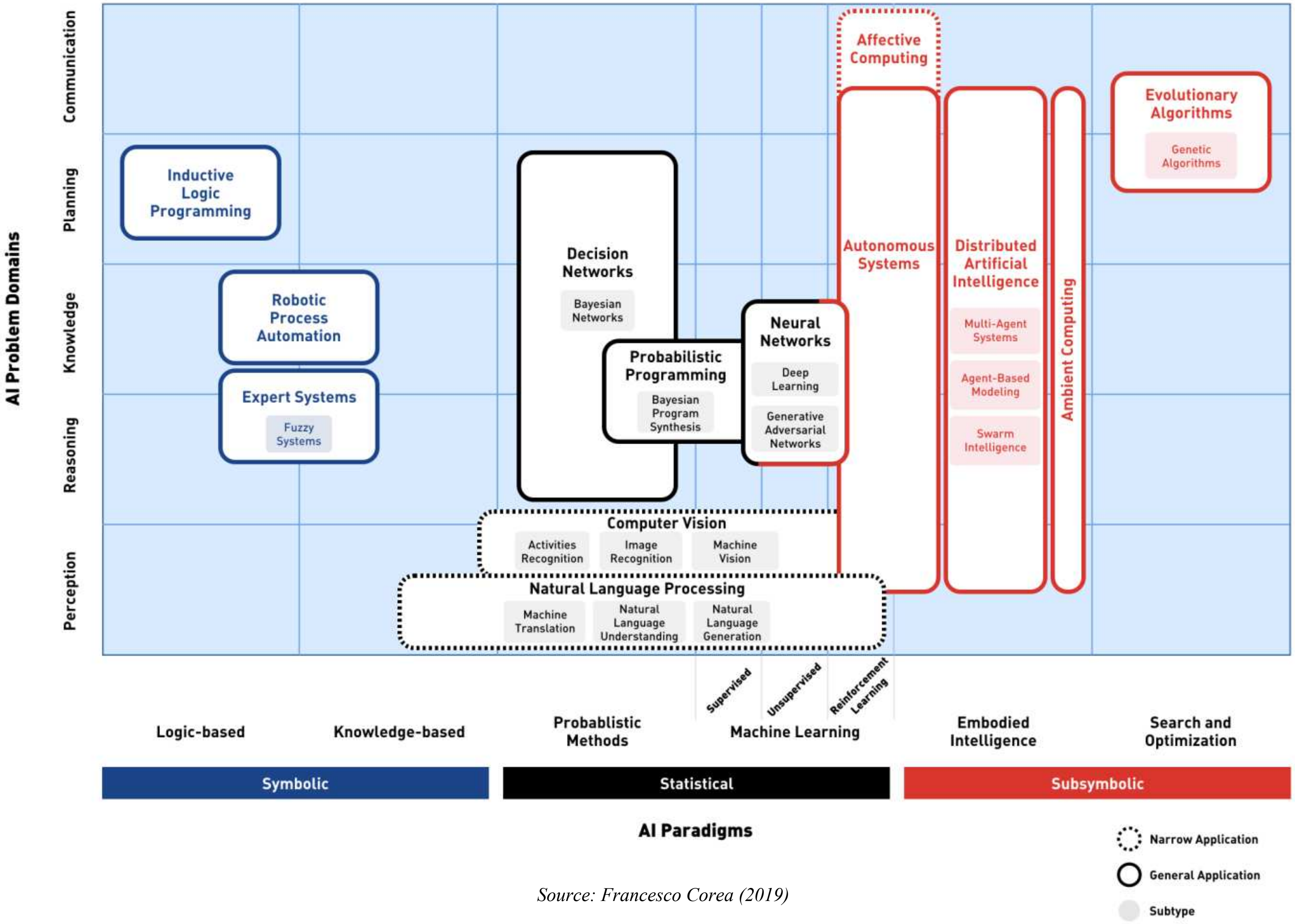
2.3. AI paradigms

AI is a broad field that encompasses several paradigms, technologies, methods, and subfields. According to Russell & Norvig (2021), when perceiving AI, academic perspectives tend to fall into two broad categories: those who consider AI through the lens of thought processes and reasoning (i.e., systems that *think* or *act* strictly rationally through symbols, rules, and world representations); and those who measure AI performance success in terms of fidelity to the human nature (systems that think and/or act humanly). Additionally, and following Haenlein & Kaplan (2019), it is possible to classify Artificial Intelligence into analytic, human-inspired, or humanized AI — depending on the type of intelligence it exhibits (cognitive, emotional, or social respectively) or according to its evolutionary stages:

- **Narrow AI (ANI):** systems that operate few tasks within a limited scope of abilities
- **General AI (AGI):** the capacity of machines to consciously think
- **Artificial Super Intelligence (ASI):** machines that can surpass all human capabilities

According to Corea (2019), Artificial Super Intelligence (ASI) is still speculation to date; general AI is the final goal of researchers, and narrow AI is what we actually have today — a set of technologies that cannot cope with anything outside their scope. Realizing the various ways AI could be classified, the author proposes the *AI Knowledge Map* (fig. 2.1.) to better understand how the field is organized. This toolbox is particularly helpful for the aim of this research since it promotes a better understanding of the subfields of AI and the problems it can address. Briefly, this map places some of the most relevant AI technologies recurring to two variables: on the one side, the AI paradigms (i.e., approaches used to solve specific AI-related problems) — which fall into logic-based tools, knowledge-based tools, probabilistic methods, machine learning, embodied intelligence, and search and optimization — and, on the other, the AI macro-approaches (symbolic, sub-symbolic and statistical). Although not represented in the figure below, Corea (2019) also claims attention to another relevant classification type: the analytics. According to the author, AI tools can use descriptive analytics (what happened); diagnostic analytics (why something happened); predictive analytics (what is going to happen); prescriptive analytics (recommending actions); and automated analytics (taking actions automatically). The next chapter will detail some of these concepts better. For now, the main point to highlight is that AI technologies should not be strictly labelled, as every technology result from a spectrum of complementary approaches.

Figure 2.1 – AI Knowledge Map



Source: Francesco Corea (2019)

2.4. Current state of AI: the rise of the statistical paradigm

As data becomes the new oil for the intelligent economy, modern organizations are relying on more statistical approaches of AI to collect massive amounts of data and extract insights that can help in decision-making processes (Jules, & Salajan, 2019; Kelleher et al., 2020). According to Enholm et al. (2021), companies should leverage data through AI, especially Machine Learning (ML) techniques, to promote agility in business processes, personalize customer experiences and predict outcomes with business analytics to create value and innovate their business models. Also, in educational contexts, growing research in the stream has highlighted the potential of Machine Learning (ML), along with other advanced analytic techniques such as Deep Learning and Artificial Neural Networks for educational purposes (Doleck et al., 2020; Feng & Law, 2021). For this reason, special attention should be paid to these technical concepts.

Briefly, Machine Learning (ML) is a subfield of AI in which computer agents, aided by algorithms, 'learn' from large amounts of data, identify its patterns, and train models accordingly, towards the ultimate goal of making accurate predictions (Kelleher et al., 2020; Russell & Norvig, 2021). Note that for the process of exploring data we call *Data Mining*, while for retrieving knowledge from the data, we call *Learning Analytics*. These concepts will be helpful later on.

The way ML performs depends on the methods it uses. In *supervised learning*, algorithms operate in pure inductive learning logic, wherein assumptions are given by previously labeled data — usually defined by a programmer or an analyst (Perrotta & Selwyn, 2020). Russell & Norvig (2021) stresses that supervised learning methods are particularly useful for regressions and classifications, playing an important role in *Predictive Data Analytics*. According to Kelleher et al. (2020), *Predictive Learning Analytics* is the process in which algorithms extract patterns from historical data and, over that basis, construct models that allow for future predictions. This concept is particularly relevant today due to the practical applications it enables. For instance, predictive analytics models can be trained to support businesses in price prediction — with algorithms automatically adjusting prices according to external factors such as seasonal changes or shifting customer demand (Russell & Norvig, 2021). In medicine, these models can be trained to assist doctors in decision-making, predicting optimal dosages, or supporting professionals in making better diagnoses supported by extensive collections of historical examples (Kelleher et al., 2020). In more trivial aspects, these models can be found in web searches, content filtering on social media, or in recommendations on e-commerce websites, playing an increasing role in the development of consumer products (Lecun et al., 2015). For the particular interest of this study, in educational contexts, predictive analytics models can support educational decision-makers in critical issues such as enrollment management and curriculum development (Doleck et al., 2020a).

However, as emerging phenomena such as Big Data — characterized by its five characteristics, i.e., large volume, large variety, high speed, high veracity, and high value (5V model) — become part of modern reality, supervised learning techniques may not work as efficiently (Fam et al., 2019; Marr, 2015). According to Zhang et al. (2018), over 75% of big data is unstructured. Even in cases where labeling large data sets may seem feasible, there is usually the challenge of scarce or expensive human labor. This has led to a renewed interest in ML paradigms that reduce the dependence on labeled data, such as unsupervised and reinforcement learning.

In *unsupervised learning*, algorithms detect potential clusters in data that have not been previously labeled. This method allows algorithms to build generative models, such as realistic text, images, audio, and video, rather than merely predicting labels for such data (Russell & Norvig, 2021). In turn, in *reinforcement learning*, data is sorted based on an intermediate trial-and-error method, mediated by its feedback (Corea, 2019; Perrotta & Selwyn, 2020; Russell & Norvig, 2021). Playing a significant role in reinforcement learning applications, Deep Learning (DL) has become one of the most active points in the field of ML since it was presented in 2006 (Zhang et al., 2018).

According to Russell & Norvig (2021), Deep Learning is a broad family of ML techniques in which a complex set of algebraic circuits — organized in networks of intermediary layers called Artificial Neural Networks (ANNs) — are trained to allow all the input variables to interact in complex ways. Perrotta & Selwyn (2020) state that the operational aspects of neural networks are based on the abstract idea of human learning as a bottom-up (inductive) process that relies on observation, experimentation, and dynamic adaptation to new information extracted from data. In other words, the basic idea of DL is to simulate the processes that occur in the biological brain, where signals from multiple inputs are gathered, filtered, and then triggered by parallel neural activations once a certain threshold is reached — what we call learning. Nevertheless, despite the considerable hype around DL possibilities (Kelleher et al., 2020), these systems still cannot "learn" like humans. Rather than "knowing," the purpose of these models is focused on their "performance" (Emmert-Streib et al., 2020).

According to Zhang et al. (2018), the bottleneck of Deep Learning lies on the promise that it can address the aforementioned challenge of Big Data. In fact, this method proves not only to be effective with large amounts of data as it requires them to work effectively (Corea, 2019; Emmert-Streib et al., 2020). For example, in the medical field, Deep Learning, through image recognition techniques, has outperformed and supported human experts in predicting breast cancer, relying on vast amounts of image data to detect signs of the disease (McKinney et al., 2020; Miao et. al, 2021). When applied to educational purposes, evidence is still missing if Deep Learning models outperform other machine learning methods (Doleck et al., 2020). According to Morgan et al. (2016), AI technologies and Learning Analytics are currently more a matter of interest than a priority in most institutions for higher education. Indeed, it is important to understand that despite the considerable hype around AI and its promising techniques, various challenges remain to be addressed. Against this background, it is important to reflect: where does AI stand in education, and where is it heading?

Chapter III – Artificial Intelligence in Education

The formal birth of Artificial Intelligence in education (AIEd) as a research field dates thirty years ago when the first issue of the journal IJAIED was released (Pinkwart, 2016). According to Roll & Wylie (2016), since then, the aim of the AIEd community has been focused on understanding and creating systems that could effectively replicate one-on-one human tutoring. Thus, this in-depth field embeds in the interdisciplinarity of AI, addressing methods and tools from several disciplines for educational problems (Feng & Law, 2021). Current definitions have highlighted data's importance and ethical use to understand students' learning behaviors and improve learning systems (Feng & Law, 2021). To realize the full potential of Artificial Intelligence in education (AIEd), this section compiles different approaches regarding using intelligent systems in the education sector. Moreover, following the model presented by Simon Sinek in the book *Start with Why* (2011), the impact of AI in education will be analyzed through three fundamental questions: firstly, the *why*, then the *how,* and finally, the *what.*

3.1. Why AI in Education?

The current use of Information and Communication Technologies (ICT) to support teaching and learning has increased the attractiveness of implementing emergent technologies such as AI in education. Recent systematic literature review studies highlight that during the last decade, and particularly in the previous two years, research in the field of AIEd has almost doubled (Bozkurt et al., 2021; Feng & Law, 2021). This trend seems to have become even more pronounced with the impact of COVID-19 and successive lockdowns that brought new challenges for schools and accelerated the development of paradigms such as e-learning, flipped learning or Massive Online Open Courses (MOOC) (Aidoo et al., 2022). On top of this, the latest technological advances in ML, LA, and Data Mining (DM), embedded in new paradigms such as Big Data, IoT and 5G, are leading to an increase in data accumulation, and the education sector is no exception (Jules & Salajan, 2019).

In light of this steep trend, researchers warn that as Pandora's box begins to open, there is no longer way to ignore that AI will increasingly become part of the educational landscape. It is therefore relevant to evaluate the impact of these technologies in the sector in a comprehensive manner, considering both the positive and negative effects.

3.1.1. Benefits of AIEd

Most scientists and researchers support the idea that AI tools can bring many benefits to education. As reported by Miao et. al (2021) in *UNESCO's AI and education: guidance for policy-makers,* if the potential of AIEd is fully realized, it can ultimately put us closer to the 4th sustainable development goal (SDG) for 2030 proposed by the United Nations: "ensure inclusive and equitable quality education and promote lifelong learning opportunities for all." Indeed, the biggest promise of this field, heralded as the driving force behind the 'fourth education revolution' (Seldon & Abidoye, 2018), lies in the idea that these technologies can extend access to high-quality education to a broader number of students worldwide (Miao et. al, 2021; Yao & Yang, 2020).

But the interaction between AI in education does not only stand for learning. Baker et al. (2019) identify three broad categories for AIEd technologies: *learner-facing AI*, *teacher-facing AI*, and *system-facing AI*. Briefly, the first category concerns AI-based tools that enhance learning; the second empowers teachers and improves teaching and assessment processes; and the third includes intelligent systems designed to support the management of educational institutions.

Starting with learner-facing AI, one of the most emphasized benefits is that these technologies allow the creation of individualized and personalized learning paths based on students' individual characteristics. In line with Renz & Hilbig (2020), learner-facing systems can ultimately help overcome the one-size-fits-all model and enhance students' learning, engagement, and motivation. In addition, researchers have highlighted other positive aspects regarding using AIEd tools for learning purposes. For example, (1) the improvement of classroom dynamics and student motivation (Hilbig et al., 2019; Tahiru, 2021; Yao & Yang, 2020), (2) the facilitation and promotion of closer collaboration between students, regardless of spatial constraints (Baker et al., 2019; Feng & Law, 2021), (3) the facilitation of distance education (Yao & Yang, 2020); or (4) the support of special education needs (Drigas & Ioannidou, 2013; Smuha, 2020; Yao & Yang, 2020).

The term 'special educational needs' refers to a vast spectrum of difficulties that cause problems in learning. According to Drigas & Ioannidou (2013), AI techniques can be used to diagnose learning difficulties, which can ultimately help to decide the most appropriate intervention method for the student. AI techniques can be used to diagnose learning difficulties, which can ultimately help to decide the most appropriate intervention method for the student. For example, AI-powered wearables can help students with physical disabilities with tasks such as reading books or recognizing faces, while technologies such as augmented and virtual reality (AR/VR) or robotics can improve learning processes in students with health disabilities or mental health issues (Smuha, 2020).

Moving on to teacher-facing systems, one of the main benefits related to the use of AI to support teaching is the possibility of real-time monitoring of classes. According to Albó et al. (2022), data analytics in education, especially in the form of learning analytics (LA), has been a point of attraction for learning technology researchers and practitioners worldwide over the last decade. As Smuha (2020) states, AI algorithms provide teachers with real-time information about students' learning patterns, allowing them to improve the quality of each individual student's learning experience sustained in data-driven evidence. This opens way for instructors to better understand each student's aptitudes and needs, as well as identify patterns of learning inside and outside the classroom (Baker et al., 2019; Yao & Yang, 2020). Moreover, the data collected can be relatively straightforward — e.g., personal details or usergenerated content produced in tasks or assignments — or more detailed, like verbal or emotional responses to the same tasks or assignments (Jules & Salajan, 2019).

Still concerning teaching applications, AI can also provide automated feedback, for example by giving insights to teachers or extra help to students. This could relieve educators, for example, from having to answer the same questions over and over again (Baker et al., 2019; Miao et. al., 2021). Yao & Yang (2020) also highlight that real-time automated feedback breaks the constraints of time and space that limit the traditional learning model, opening new opportunities for teacher-student interaction.

Researchers have also highlighted the potential of AI to broaden horizons for more innovative pedagogical approaches (Smuha, 2020). According to Baker et al. (2019), these technologies can be used, for instance, to support flipped learning practices. For example, students become familiar with new concepts through intelligent tutoring systems outside the classroom and later, in class, teachers can make better use of their time by delving deeper into the subjects.

Lastly, special emphasis has been laid on the benefit of AI to relieve teachers by automating repetitive and administrative tasks, such as plagiarism detection, administration, feedback, or assessment (Jules & Salajan, 2019). For example, Artificial Intelligence can be used to promote more frequent formative assessments, taking the burden off summative exams without increasing teachers' workload. In the same vein, Smuha (2020) states that AI enables innovation for standardized evaluation, allowing teachers access to a broader scope of student skills and increasing the relevance of assessments to the skills that will become more important for this VUCA world.

As far as system-oriented AI is concerned, the main benefits are associated with the possibility of automating and managing school administrative tasks. In particular, AI technologies can record teacher and student attendance (Jules & Salajan, 2019), increase campus security by blending AI with traditional video surveillance (Yao & Yang, 2020), or even reduce school dropouts. According to Smuha (2020), ML methods can facilitate and support teachers and schools by detecting and predicting which students are at risk of early failure. For example, by notifying the teacher about the failure rate level, these algorithms can give them possible corrective measures in case it is below expected or more challenging if the class is overachieving (Jules, & Salajan, 2019). Hilbig et al. (2019) also draw attention to the possibilities of LA and ML to enhance the school curriculum.

3.1.2. Barriers of AIEd

Despite all the hype surrounding the possibilities of AIEd, researchers have raised concerns regarding the risks of the mass deployment of such powerful technologies in educational settings (Yao & Yang, 2020). In line with Saville (2012), when analyzing the impact of digital technologies in the sector, it is fundamental to consider that such a large and complex system carries multiple dynamics that occur at various layers. Therefore, the consequences of this impact must be read from a macro-micro perspective.

Starting with one of the most significant challenges at the macro level, the literature has highlighted that the limited evidence and consistency of scientific research regarding the actual effects of these technologies for educational purposes still compromises the development of the field (Baker et al., 2019). In line with these authors, one reason for this is the reduced public funding in Research and Development (R&D) for AIEd, which still lags behind other sectors. Just take the example of AI in healthcare. This market is currently valued at USD 15.1 Billion in 2022 and projected to reach USD 187.95 Billion by the year 2030 (Statista, 2022). In Fintech, for instance, the global impact of AI in the market was valued at USD 10.14 billion in 2021, with an estimated compound annual growth rate (CAGR) of 15,8% between 2022 and 2028, and a forecast of USD 28.11 billion by the end of the reporting period (BlueWeave Consulting and Research Pvt Ltd., 2022). In turn, in AIEd, the market size was valued at USD 2 billion in 2021, with a projection for 2030 of USD 80 Billion (CAGR of 45%), according to Global Market Insights (2022).

In parallel, research has pointed for a lack of clarity and agreement concerning AI ethics guidelines, especially in the field of education. At the 22nd International Conference of AIED (Roll et al., 2021), Cathy Adams and other researchers warned about the underdevelopment of K-12-specific documents compared to AI in general. An unclear direction in such a wide, complex, and interdisciplinary field as AIEd can lead to conflicts of interest and leakage between stakeholders (Mertala et al., 2022; Popenici & Kerr, 2017). A study conducted by Jobin et al. (2019) aimed to understand the global landscape of AI ethics guidelines in the education sector. The results showed that although many guidance documents have been issued among the public and private sectors, the solutions to address AI ethical problems diverge significantly. This discrepancy is even sharper between geographic areas (e.g., the west and east, the global north and south, urban, and rural). This phenomenon, also called by Jules & Salajan (2019) as "digital frontierism", brings up Galtung's idea that a deep structural imperialism divides the world into core and peripheral regions, with digitalization being a possible driver for widening this gap.

According to Chetty et al. (2018) digital divide is usually characterized by two fundamental issues: limited and costly infrastructure and reduced digital literacy in low/middle income communities. Along the same line, Yao & Yang (2020) state that the high cost of AI can contribute to the lack of resources and knowledge in underdeveloped regions. Also worthy of note are sociodemographic factors which can also be related with possible gaps in digital literacy (Haenlein & Kaplan, 2019). These polarities pose a complex challenge to modern societies since the core and success of AI depends on humanization, collaboration, and justice.

Data-related issues are also of concern to researchers, education stakeholders, and policymakers worldwide. According to Jules & Salajan (2019), education has been progressively powered by data, especially with the rise of international tests and rankings. The authors stress that this pushes the global education agenda to collect, explore, share, and compare information to improve access to schools and increase the quality, accountability, and efficiency of national education systems. Note that this is not inherently a dangerous phenomenon: data sharing can foster a more ethical, inclusive, efficient, and transparent system of research (Jules & Salajan, 2019). However, if misused, the mining of large amounts of data, which are required for the efficiency of modern AI techniques such as ML, can conflict with the privacy and security of their users (Baker et al., 2019; Yao & Yang, 2020). These risks become even more delicate when children are at stake. But what particular problems can be related to data?

In the first instance, researchers call to action on data ownership issues and accountability: indeed, who controls data and who assumes responsibility (Baker et al., 2019; Tahiru, 2021; Yusri et al., 2020)? Still concerning this topic, Zhang et al. (2018) mention that Big Data is an information source that often presents noisy, incomplete, inaccurate, and redundant objects. This can trigger other challenges, such as overlapping decontextualized and unbiased data that can affect the performance of ML and DL and therefore their results (Baker et al., 2019). Lastly, it is increasingly more difficult for humans to understand the inner complexity of AI techniques such as DL. According to Kaplan & Haenlein (2019), Deep Learning is inherently a *black box* — which means that while obtaining results is relatively simple, the process of DL is largely opaque to humans. This barrier can compromise decision-making processes, as they are supported by a logical process and data to which, to a large extent, people don't have access (Baker et al., 2019). Roll et al. (2021) add that this data opacity can be intentional (e.g., regarding secrecy or competition); due to technical illiteracy; or related to the scale of application, for example, in a situation involving many programmers or methods. In this regard, some ethical principles need to be addressed: (1) transparency; (2) justice and fairness; (3) security (i.e., non-maleficent); (4) liability, (5) data privacy, (6) and the promotion of beneficence, freedom, and autonomy (Roll et al., 2021).

In parallel, as data becomes more available, non-education players are gradually entering the education market, seeking to solve the sector's biggest problems and create societal opportunities. As Jules & Salajan (2019) state, although the commercialization of education is a controversial topic, it is a growing reality. The EdTech industry, in particular, has grown exponentially, especially with the need for new digital and flexible solutions that the pandemic has forced. The European EdTech Funding Report 2022 (Brighteye Ventures, 2022), highlighted that since 2020, funding in EdTech companies had been awakening from all spectrums of investors and governments. The results pointed to the maturing of the EdTech market, with an increasing number of unicorn companies emerging not only from the US, Chinese, and Indian markets but also from the European Edtech scene. From 2020 to 2021, the results showed that the average deal size in Europe stepped up considerably, almost tripling from $2.9 million in 2020 to $8.4 million in 2021.

It is important to consider that the AIEd and EdTech industries also face very specific barriers. These include the need for reforming EdTech policy (Nemorin et al., 2022); organizational readiness (Tahiru, 2021); or the high cost of AI and upfront R&D costs (Baker et al., 2019). In addition, Baker et al. (2019) highlight the following factors: inner characteristics of a fragmented marketplace and a complicated system; the lack of expertise; lack of generated return when compared to other markets that are currently investing in AI; lack of public investment in AIEd; and lack of single point of government leadership.

Considering the ethical barriers, as education is being increasingly premised upon marketized approaches, several voices question whether emergent technological solutions can actually improve efficiency and educational outcomes rather than increase inequalities (Gorur et al., 2019; Pedró et. al, 2019). Authors like Neves & Holmes (2020) warn for the dangers of the rise of the "techno-solutionist" paradigm in global discourses, which presents technology as the "solution" to the world's most complicated problems, such as those that arising from education (Milan, 2020). Similarly, Popenici & Kerr (2017) reflect on an important issue: who will set the educational agenda for the future – educational institutions or educational technology enterprises? Furthermore, will data mining and analytics be used on behalf of revenue or the learner?

Another pertinent issue that has generated controversy not only among researchers but also in common sense concerns the possibility that AI contributes to the increase in unemployment (Hoeschl et al., 2018). According to UNESCO IITE. (2020), technology is far from replacing teachers. Indeed, an apparent agreement seems to reside in the teacher's fundamental role in building digital skills and unlocking the potential of these technologies to improve teaching and learning. However, some barriers need to be overcome to prevent this risk from becoming a reality. As Baker et al. (2019) stress, one of the biggest challenges to address is teachers' lack of confidence and skills, which is generally related to insufficient mechanisms and a lack of available specialized training. This problem often refers to teachers being burdened with excessive workloads and administrative tasks, which affects their well-being and motivation to learn new technologies. However, another issue has been stressed: the overall lack of knowledge about AI, including educators and trainers, especially regarding more complex concepts such as Learning Analytics or Machine Learning. According to Luckin et al. (2022), most people in education and training are largely unaware of what AI is and the significant changes these technologies will bring over the next decade. Ferguson (2012) advise that the lack of scientific evidence on LA can reflect other issues: for example, (1) lack of geographical knowledge spread (with almost no evidence coming from less developed regions); (2) gaps in peoples' knowledge (for instance, regarding ethical practices and applications in informal learning); (3) little understanding about the learning analytics cycle; and (4) little evaluation of commercially available tools.

According to Luckin et al. (2022), in the educational scenario, there is a growing recognition that some of the educational problems can be improved with the help of AI. Yet, the general lack of knowledge on the topic seems to prevent schools and teachers from making these decisions, which has been reflected in a critical gap between what AIEd technologies can do and how they are actually implemented (Bates et al., 2020; Kabudi et al., 2021). Coupled with this issue, a growing body of evidence has been reinforcing the idea that perceptions and feelings associated with technologies can pose major challenges not only for practical implementation reasons, but also in people's own willingness to learn about AI. For example, in a study conducted by Renz & Hilbig (2020), results showed that lack of knowledge in AI usually reflects either in people getting overwhelmed or uninterested in AI's technical potential, making them take either a passive or negative attitude towards this topic. In the same vein, Ayanwale et al. (2022) state that feelings associated with AI can take the most varied forms, from blind positivity, discomfort or even to what researchers call as AI anxiety. The authors stress that this last feeling is generally related to factors such as little understanding about the differences between human and computational intelligence, to the fear that machines might replace humans, or to the fact that the vague way these technologies seem to be designed. According to Mertala et al. (2022) people's conceptions regarding these technologies often reflect public representations of AI and narratives surrounding it.

3.2. How can AI be leveraged to enhance education?

Having framed the promises and implications of the *why,* a second fundamental question should be raised: *how* to expand AI in education while minimizing its risks and optimizing its benefits? An integrated set of actions has been highlighted throughout the literature.

First, it is crucial to increase funding for AI and foster coordinated policy guidance to promote the integration of AI in the education sector (Baker et al., 2019). According to Yao & Yang (2020), the successful implementation of AI in the global society depends heavily on capital investment, supported by national policies and government leadership.

However, upstream support is not enough. According to Baker et al. (2019), there must be an active and closer collaboration between every stakeholder, both in a top-down and a bottom-up sense. This includes educational institutions, teachers, EdTech companies, researchers, developers, learners, and many other agents of change, in order to promote a sustainable integration of AIEd technologies into the educational landscape. In particular, since companies are designing most AI-based solutions, the authors suggest that the EdTech industry should promote a test-based environment, for example, with entreprises providing clear incentives to trigger teachers' engagement while testing their solutions in real settings. This will create a more transparent and reliable system that considers the needs of every stakeholder — making companies closer to achieving the desired sustainable competitive advantage while empowering schools and teachers to make more informed decisions regarding the technology they want to purchase and use (Baker et al., 2019). Additionally, there should be an explicit ethical conduct behind AIEd that guides the use and accountability of data. The government should publicly state its ambition to create a reliable system of educational data sharing in the short to medium term, highlighting the clear consequences related to the misuse of AI in educational settings (Baker et al., 2019).

Considering that the introduction of ICT in society is making the labor market progressively more demanding, Yao & Yang (2020) reinforce the importance of enhancing the national education level and investing in training professional talent. For the particular scope of this research, teachers need to be trained for AI, not only to understand the potential of these systems and how to use them, but also to ensure that it enters the discussion of all subjects (Neves & Holmes, 2020).

Finally, and still regarding this micro-universe, teachers' confidence and skills must be pumped up. According to Baker et al. (2019), to increase the general knowledge about Artificial Intelligence, education must go in three complementary directions: learning 'about', 'with', and 'for' AI. According to the authors, learning 'about' AI involves teaching students how to create and develop ethical applications of these technologies. Regarding learning 'with' AI, the authors refer to the use of Artificial Intelligence as a support for teaching and learning practices. Finally, learning 'for' AI concerns empowering people to better understand the implications of such technologies both for present and future societies (Baker et al., 2019; Neves & Holmes, 2020).

3.3. What are the applications of AI in education?

Research shows that the majority of AIEd applications are student-facing (Miao et. al, 2021), with Intelligent Tutoring Systems (ITS) being the most researched and available AIEd application (Feng & Law, 2021). As mentioned above, ITS are systems that provide customizable and immediate feedback to the learner (Xu et al., 2019). In other words, by collecting and analyzing the learner's data, this system is able to provide an optimal path for a given module or subject considering each student's cognitive, motivational, and emotional aspects (Neves & Holmes, 2020; Jules & Salajan, 2019). ITS are usually supported by ML techniques, artificial neural networks, and self-training algorithms, which allow them to automatically adjust the difficulty level as the student engages with it (Miao et. al, 2021). These systems have been particularly highlighted in supporting self-regulated learning (Ingkavara et al., 2022).

Looking for practical applications, large-scale empirical studies have showed that Intelligent Tutoring Systems applied to Text Structure Strategy (ITSS) can produce successful outcomes at 4th, 5^{th,} and 7th grades (Wijekumar et al., 2017). Briefly, this type of ITS provides structure-based instruction in text structure strategy with the aim of helping students in comprehension-based activities such as summarizing, inferring, elaborating, and applying. The results of the study applied to 7th grade revealed that at the end of one school year of using ITSS, the reading comprehension levels of students in 108 rural and suburban school classrooms improved when compared to the initial standardized reading levels (Wijekumar et al., 2017).

The effects of ITS have also been studied in preschool settings, as shown in the studies by Gulz et al., (2020) and Zhang & Aslan (2021). But these systems go far beyond learning. For example, teachers can use them to harvest important insights concerning learners and their engagement behavior, to automatize assessment and evaluation processes, or even to model and predict students' performance in a game-based learning environment (Miao et. al., 2021).

According to Belpaeme et al. (2018), the use of robots in education is also being explored, most prominently in special education. In particular, Jules & Salajan (2019) reinforce the idea that robots can correct children's errors and reinforce accurate information without overemphasizing them. For example, humanoid robots with speech capabilities can help students on the autism spectrum develop their communication and social skills (Miao et. al., 2021). If such robots are equipped with a digital recording device, they can also create a database of verbal responses and add sensors, ultimately allowing them to digitize emotional responses (Jules & Salajan, 2019). Telepresence robots have also been outlined to help students with special needs attend school at home or in the hospital or during emergencies or crises (Miao et. al., 2021).

Another example of a student-facing AI tool is the dialogue-based tutoring system (DBST) which, mainly supported by natural language processing techniques, gives feedback to students towards the simulation of a conversation. Despite the small representation of DBTS (most exist within research projects), they are particularly useful for inquiry-based pedagogical approaches (Miao et. al., 2021).

Regarding teacher-facing AI, far less attention has been given to it in comparison to student-facing AI. Most applications rely on AI-powered teaching assistants designed to reduce workload and time-consuming tasks, such as taking attendance, marking assignments, and improving classroom dynamics. For instance, smart scoring is already impacting traditional assessment — plagiarism software can be used to detect blank papers, plagiarism, or identical papers, shortening a lot of time for teachers (Renz & Hilbig, 2020; Yao & Yang, 2020). Another example is an AI-based platform that helps teachers to create optimized seating charts according to pupils' behavior and classroom dynamics (Baker et al., 2019). Teacher-facing AI also includes platforms that compile students' information and data. This can be provided, for example, by ITS or through biometric recognition technology which recognizes students' expressions and provides information regarding students' engagement, attention, and participation historic (Yao & Yang, 2020).

Lastly, regarding system-facing systems, practical implications can include educational tools that support school administration with the automation of administrative tasks such as hiring and admissions (Neves & Holmes, 2020), managing teachers (Renz & Hilbig, 2020), or registering teachers' and students' attendance. It can also support time management tasks: for example, by automatically creating a school's timetables to address its organizational and financial needs, as well as the human need of teachers and students (Neves & Holmes, 2020).

Chapter IV- Theoretical Approach

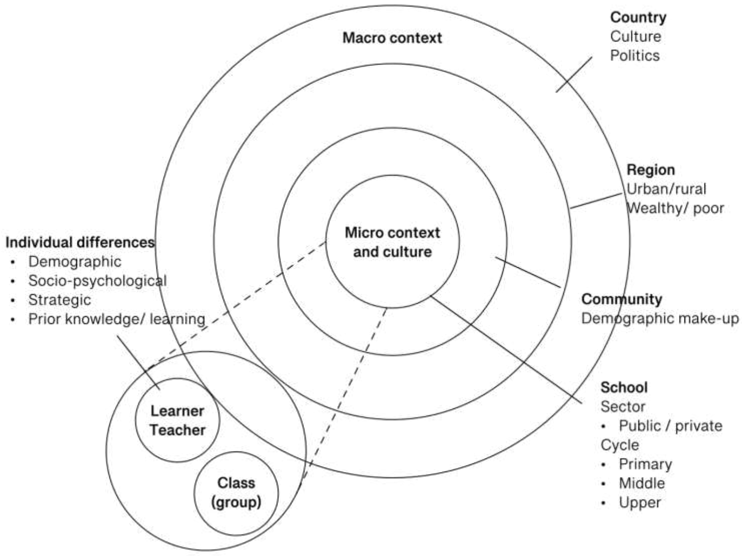
The previous framework provided an overview of relevant theoretical understandings related to the main topics of this thesis. This allowed for a deeper understanding of the research problem, framing it within the aim of this study — understanding the impact of AI on education. According to Campenhoudt, Quivy & Marquet (2021), the literature review is a crucial moment in the research process, as it is where the theoretical perspective that is intended to be adopted to answer the research question is conceived.

To summarize the literature's key points, the idea that AI can improve some of education's most significant problems and innovate teaching and learning practices has led to a keen interest in the topic (Popenici & Kerr, 2017; Renz & Hilbig, 2020; Miao et. al., 2021; Yao & Yang, 2020). So much so that the interaction of AI in this sector is already beginning to take shape with applications geared toward students, teachers, and systems (Baker et al., 2019). Student-facing AI has covered the vast majority of applications (Feng & Law, 2021), ranging from ITS that automatically support and personalize student's learning experiences to VR/AR or even robots that, embedded with computer vision and natural language processing capabilities, can greatly aid special education (Neves & Holmes, 2020; Renz & Hilbig, 2020; Miao et. al., 2021). For educators, the potential of AI lies in a deeper understanding of students' strengths and weaknesses, greater engagement in the classroom, or the reduction of massive administrative work-a common ground with system-oriented AI solutions (Baker et al., 2019; Renz & Hilbig, 2020; Yao & Yang, 2020). In any case, implementing these systems still entails several barriers emerging from the various touchpoints of the educational sector, which can ultimately compromise an effective and ethical integration of AI in this landscape. Against this background, a research question was proposed to analyze these technologies' positive and negative effects on the education sector.

RQ – What is the possibility of implementing AI in Portuguese primary and secondary schools?

Taking the hierarchical educational model proposed by Saville (2012) (see next figure), the educational sector is a broad, complex, and heterogenous system, with multiple dynamics occurring from the school level to the wider context in which it resides. Therefore, to answer the present research question, the scope of this study focuses on a micro-macro approach, as it aims to understand the broad effects of AI in schools from a particular lens – in this case, teachers.

Figure 4.1 – Context in education: a complex dynamic system



Source: Adapted from Saville, N. (2012)

When considering the implementation of AI technologies in the education field, several factors, narrow and broad, can influence its success. For example, from a micro perspective, empowering schools and teachers with training can make them more knowledgeable and confident with AI and thus help them to make more informed decisions regarding the best solutions to use (Baker et al., 2019). Considering the risk of the rise of digital frontierism (Jules & Salajan, 2019), this investigation starts by hypothesizing whether sociodemographic factors affect knowledge about AIEd and, more particularly, where those differences are.

Following this hypothesis, the next step is to understand the impact of *specific* positive and negative factors, such as the training issue mentioned before (Baker et al., 2019; Ferguson & Clow, 2017), as well as *broader* ones such as ethical challenges (Roll et al., 2021), data implications (Baker et al., 2019; Roll et al., 2021; Tahiru, 2021; Yao & Yang, 2020), or even challenges pertaining to other industries, such as those of EdTech (Baker et al., 2019; Tahiru, 2021; Brighteye Ventures, 2021). As highlighted in the literature, there is a need for tighter collaboration between those who develop AI-based solutions for education and those who use them (Baker et al., 2019). For this reason, and since this thesis is set within the management background, these factors will also be considered, as further detailed.

Finally, to expand the results obtained, the last hypothesis referring to the same research question intends to understand which feelings emerge from the research problem. In line with studies that show that sentiments affect how digital solutions are received in education (Renz & Hilbig, 2020), the last part of the research aims to understand which feelings contribute most to the possibility of implementing AI in Portuguese primary and secondary schools.

The next chapter will provide a more in-depth description of the methodological process of the research, detailing the research objective, question, and the hypotheses raised.

Chapter V – Methodology

5.1. Research Design

Research methodology follows procedures and practices based on the scientific method in order to increase understanding and create valid knowledge. Thus, the reliability and validity of a study depend on proper conduct and a strong connection between its research objective(s) and methodology(s), as well as a logical interpretation and analysis of the data collected (Garg, 2016). Kothari (2016) suggests that despite research studies follow specific purposes, their objectives tend to fall into four broad groups:

- Get new insights or familiarity with a phenomenon (*exploratory / formulative studies)*.
- Portray the characteristics of an individual, situation or group (*descriptive research studies*).
- Understand the frequency of a phenomenon and possible associations (*diagnostic studies*).
- Test a hypothesis of a causal relationship between variables (*hypothesis-testing studies*).

As far as the present research is concerned, its objective lies in both the first and last categories as it intends to become familiar with the study phenomenon while determining, under inductive reasoning[3], consistent patterns of causality among the variables identified in the literature review. Thus, and following the scientific method, this study is divided into two parts: one theoretical and one empirical.

Starting from the theoretical part, exploratory research was conducted to review the literature about AI, its paradigms, and application in educational settings. This analysis relied on secondary data sources (articles, books, reports, websites, etc) and enabled the formulation of a set of hypotheses that emerged from the research objective. To ensure reliability and validity of sources, recent articles (5 years or less) and from reliable journals were favored.

To empirically substantiate this theoretical framework, in the second part, a questionnaire was conducted and used as a primary source of data to test these hypotheses (see Appendix C). To ensure the validity of the survey, its indicators were supported in the literature review and validated by supervisors. Subsequently, a pre-test was conducted with the help of four teachers.

Finally, a mixed research design approach was used to validate the hypothesis, resorting to methods such as Descriptive and Analytics statistics, a SEM-PLS approach and a Sentiment Analysis, as will be further detailed. The table below presents the relationships between the research objective, research question, hypothesis, methodology and references.

[3] *Inductive* research does not aim to draw true conclusions from equally true premises (as in the deductive method). Rather, this approach aims to generate meanings from the data set collected in order to identify patterns and relationships between social phenomena under analysis (da Costa, 2012; Cunha, 2021).

Table 5.1 – Relationship between the research objective, research question, hypothesis, methodology and references

Research Objective	Research Question	Hypothesis	Methodology	References
Understanding the impact of AI in education	What is the possibility of implementing AI in Portuguese primary and secondary schools?	*Sociodemographic differences influence Knowledge of AIEd*	[Quantitative] Descriptive and Analytical Statistics	Baker et al. (2019); Jules & Salajan (2019); Haenlein & Kaplan, 2019.
		The Benefits of AIEd positively influence the possibility of implementing AI in Portuguese schools	[Quantitative] SEM-PLS	Seldon & Abidoye (2018); Miao et. al. (2021); Yao & Yang (2020); Hilbig et al. (2019); Tahiru (2021); Baker et al. (2019); Feng & Law (2021); Drigas & Ioannidou (2013); Smuha (2020); *Jules & Salajan* (2019).
		The Barriers of AIEd negatively influence the possibility of implementing AI in Portuguese schools		Yao & Yang (2020); Baker et al. (2019); Chetty et al. (2018); Jobin, Ienca & Vayenna (2019); Roll et al. (2021); Jules & Salajan (2019); Mertala et al. (2022); Neves & Holmes (2020); Popenici & Kerr (2017); Nemorin, S., (2021); Hilbig et al., (2019).
		Knowledge of AIEd positively influences the possibility of implementing AI in Portuguese schools		Jules & Salajan (2019); Yao & Yang, (2020); Baker et al. (2019); Tahiru, (2021b); Zhang et al. (2018); Kaplan & Haenlein (2019); Gorur et al. (2019); Neves & Holmes (2020); Hoeschl et al., (2018).
		The sentiments associated with AI in education positively influence the possibility of implementing AI in Portuguese schools	[Qualitative] Sentiment Analysis	Ayanwale et al. (2022); Baker et al. (2019); Mertala et al. (2022); Renz & Hilbig (2020).

Source: Author's elaboration

5.2. Data Analysis tools

As previously stated, a mix of quantitative and qualitative methods are used to analyze and model the data for this investigation. The reason behind this decision relies on evidence that supports the relevance of using mixed methods rather than a single methodological approach. According to McKim (2017), mixed methods increase the validity of the results and give a deeper and broader understanding of a particular phenomenon.

According to Molina-Azorin (2016), when defining a mixed method, two factors need to be considered: priority and implementation of data collection. Concerning priority, this thesis prioritizes the quantitative part, using the qualitative approach to enrich the overall understanding of the results obtained. In particular, the core of this study lies in the SEM-PLS approach (explained further below) since this method fulfils the purpose of testing causal relationships between variables.

Regarding the implementation of data collection, Molina-Azorin (2016) adds that information can be collected in stages (i.e., different methods for different research objectives) or simultaneously — if the goal is to compare the two forms of data simultaneously to find congruent results. For the specific case of this study, the chosen methodology follows a concurrent approach, as it intends to combine both quantitative and qualitative insights into the same research question. Following this, the empirical research was divided into three parts, two quantitative and one qualitative.

5.2.1. Descriptive and Analytical statistics

The first part provides descriptive and analytical statistics about respondents' knowledge of AI, aiming to evaluate the hypothesis *Sociodemographic differences influence Knowledge of AIEd.* It is of interest for this research to assess this specific variable since knowledge mediates the relationship between respondents' perceptions of the benefits and barriers of AI concerning the possibility of implementing these technologies in Portuguese schools. Regarding data analysis tools, an ANOVA test was used to ascertain whether significant differences exist in respondents' knowledge of AI in relation to sociodemographic variables. The post hoc Tukey test was later conducted for an in-depth understanding of where those differences are. Both tests were conducted with the help of the software SPSS.

5.2.2. SEM-PLS

It is in this part that greater priority should be given. To test the hypotheses that emerged from the research question, it was used the quantitative-based *Structural Equations Model* (SEM), a path analysis modelling tool that enables to identify cause-effect linkages between latent variables (Tarka, 2018). According to Sarstedt et al. (2017) this method allows testing the predictive power of a model supported by theoretical evidence. To conduct the analysis, the SmartPLS program was used. This software resorts to the Partial Least Squares (PLS) — an example of a variance-based SEM approach that allows estimation of very complex models with considerably lower sample size requirements (Henseler et al., 2015). Below are presented the hypotheses to answer the research question of this study (*What is the possibility of implementing AI in Portuguese primary and secondary schools?*) on which the conceptual model to be tested in SEM-PLS was based (see figure 2). Table 5.2. summarizes the indicators, questionnaire questions and references.

Hypotheses and conceptual model (SEM-PLS)

H1a – The perceived benefits of AI in education positively affect knowledge of AIEd.

H1b – The perceived benefits of AI in education positively affect the possibility of implementing AI in Portuguese primary and secondary schools.

H2a – The perceived barriers of AI in education negatively affect knowledge of AIEd.

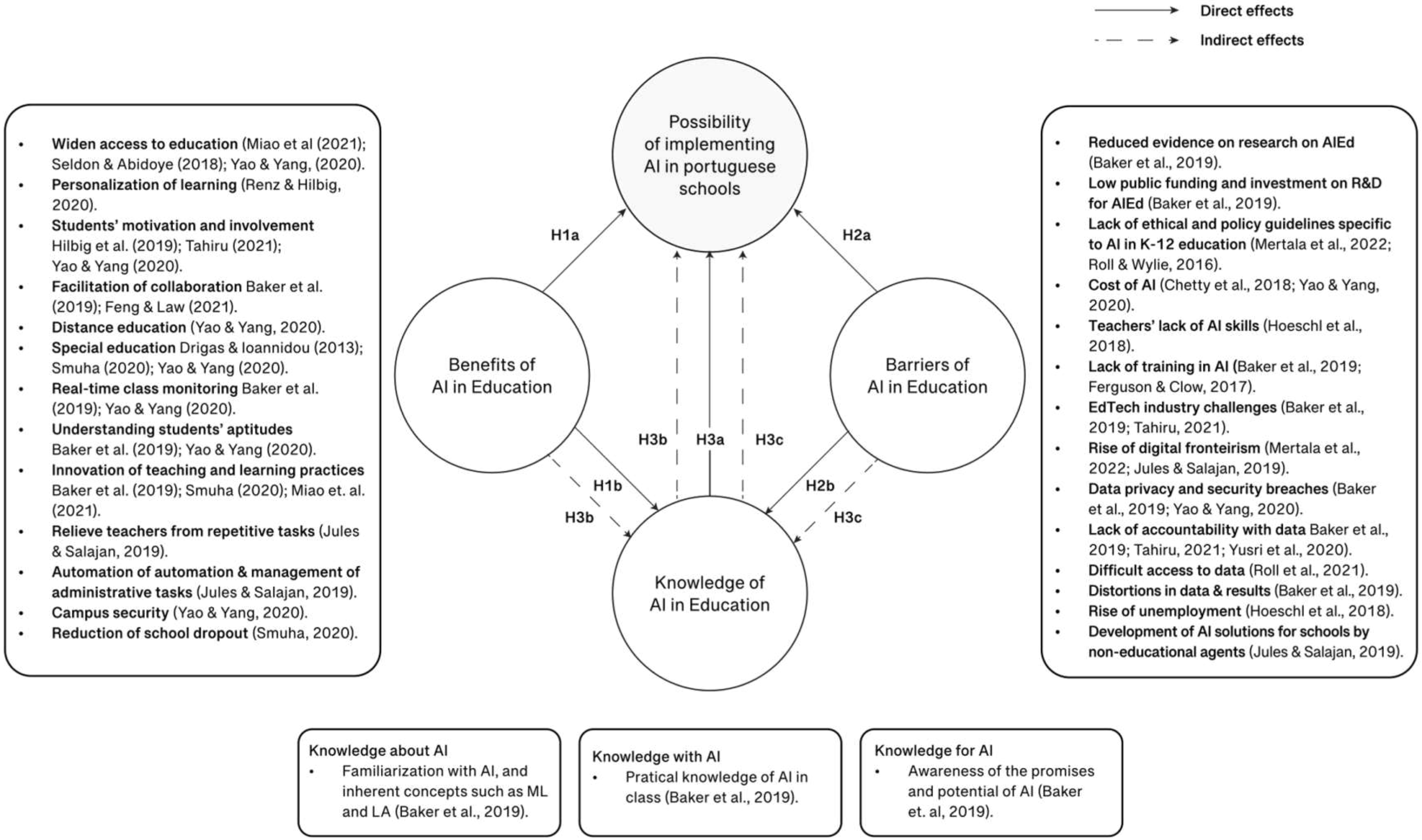
H2b – The perceived barriers of AI in education negatively affect the possibility of implementing AI in Portuguese primary and secondary schools.

H3a – Knowledge of AIEd positively affects the possibility of implementing AI in Portuguese primary and secondary schools.

H3b – Knowledge of AIEd mediates between the benefits of AI in education and the possibility of implementing these systems in Portuguese primary and secondary schools.

H3c – Knowledge of AIEd mediates between the barriers of AI in education and the possibility of implementing these systems in Portuguese primary and secondary schools.

Figure 5.1– Conceptual Model and Hypothesis for the SEM-PLS analysis



Source: Author's elaboration

Table 5.2 – Relationship between conceptual model, variables, and questionnaire

Dependent Variable	Indicator	Possibility to implement Artificial Intelligent in Portuguese primary and secondary schools.	
	Questionnaire Question	I would implement intelligent systems in my educational activity if I could.	
Independent Variables	Indicator	Questionnaire Questions (answers from 1 to 7)	References
Benefits of AI in Education	Widen access to education	Artificial Intelligence extends learning opportunities to a larger number of students.	Miao et al (2021); Seldon & Abidoye (2018); Yao & Yang, (2020).
	Personalization of learning	AI in education helps create individualized learning paths based on the specific characteristics of each student.	Renz & Hilbig (2020).
	Students' motivation and involvement	Implementing AI in educational settings helps to increase students' motivation and involvement.	Hilbig et al. (2019); Tahiru (2021); Yao & Yang (2020).
	Facilitation of collaboration	AI in education facilitates collaboration between students.	Baker et al. (2019); Feng & Law (2021).
	Distance education	AI facilitates distance teaching/learning.	Yao & Yang (2020).
	Special education	Intelligent systems can assist special education (students with greater learning difficulties and/or physical disabilities).	Drigas & Ioannidou (2013); Smuha (2020); Yao & Yang (2020).
	Real-time class monitoring	The implementation of AI technologies in the classroom allows teachers to monitor student learning.	Baker et al. (2019); Yao & Yang (2020).
	Understanding students' aptitudes	AI technologies help teachers better understand aptitudes and possible learning gaps among students.	Baker et al. (2019); Yao & Yang (2020).
	Innovation of teaching and learning practices	The implementation of AI in education paves the way for more innovative teaching and learning methods and approaches.	Baker et al. (2019); Smuha (2020); Miao et. al. (2021).
	Relieve teachers from repetitive tasks	AI helps teachers reduce the time needed to perform repetitive tasks.	Jules & Salajan (2019).
	Automation of automation and management of administrative tasks.	AI facilitates the automation and management of administrative tasks in Portuguese primary and secondary schools.	Jules & Salajan (2019).
	Campus security	AI helps reinforce safety inside Portuguese primary and secondary schools.	Yao & Yang (2020).
	Reduction of school dropout	AI technologies can help schools reduce dropout rates by detecting risky patterns early.	Smuha (2020).

Barriers of AI in Education	Reduced evidence on research on AIEd	The reduced scientific evidence on the impact of AI in education (especially in K-12) makes its integration in Portuguese schools difficult.	Baker et al. (2019).
	Low public funding and investment on R&D for AIEd	Low public investment in AI research and development in education is an obstacle to the implementation of AI in Portuguese primary and secondary schools.	Baker et al. (2019).
	Lack of ethical and policy guidelines specific to AI in K-12 education	The lack of specific ethical and policy guidelines on the use of AI in schools hinders the use of intelligent systems in Portuguese primary and secondary schools.	Mertala et al. (2022); Roll & Wylie (2016).
	Cost of AI	The high costs of implementing, maintaining, and using AI in education make it difficult to implement AI in Portuguese primary and secondary schools.	Chetty et al. (2018); Yao & Yang (2020).
	Teachers' lack of AI skills	Teachers' lack of AI skills negatively affects the implementation of these systems in Portuguese primary and secondary schools.	Hoeschl et al. (2018).
	Lack of training in AI	The lack of mechanisms and specific training on AI makes it difficult to use intelligent systems in a classroom context.	Baker et al. (2019); Ferguson & Clow (2017).
	EdTech industry challenges	Most educational technology (EdTech) companies are sufficiently developed to implement AI in their products/services.	Tahiru (2021).
		The lower return generated by AI in the education market, compared to others, makes it difficult to integrate AI into education.	Baker et al. (2019).
	Rise of digital frontierism	The implementation of AI in education accentuates inequalities between more disadvantaged areas and more developed areas.	Mertala et al., 2022; Jules & Salajan (2019).
	Data privacy and security breaches	Possible security and data privacy breaches hinder the implementation of AI in Portuguese primary and secondary schools.	Baker et al. (2019); Yao & Yang (2020).
	Lack of accountability with data	The lack of accountability with data poses a challenge to the implementation of AI in Portuguese primary and secondary schools.	Baker et al. (2019); Tahiru (2021); Yusri et al. (2020).
	Difficult access to data	The difficult access to data is a barrier to the implementation of AI in Portuguese primary and secondary schools.	Roll et al. (2021).
	Distortions in data	Possible distortions in data and, consequently, erroneous results generated by AI make it difficult to implement AI in Portuguese schools.	Baker et al. (2019).
	Rise of unemployment	The possibility of AI automating tasks performed by humans contributes to the rise of unemployment in schools.	Hoeschl et al. (2018).

	Development of AI solutions by non-educational agents	The development of AI by non-educational agents (e.g., businesses) is beneficial for the implementation of AI in schools.	Jules & Salajan (2019).
Knowledge of AI in Education	Knowledge about AI	I know what Artificial Intelligence is.	Baker et al. (2019).
		I am familiar with AI concepts, such as Machine Learning.	
		I am familiar with concepts inherent to AI, such as Learning Analytics.	
	Knowledge with AI	I am aware of how AI technologies are being implemented in educational settings.	Baker et al. (2019).
		IT tools are used in the classroom.	
		I can program AI.	
	Knowledge for AI	I believe in the potential of AI in society at large.	Baker et al. (2019).
		I think it is beneficial to implement intelligent systems in schools.	

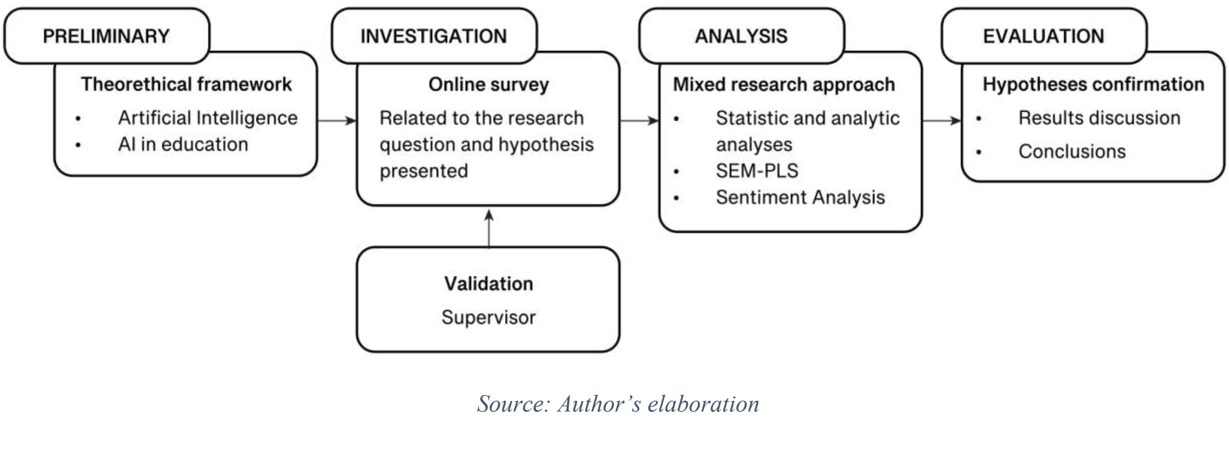
Source: Author's elaboration

5.2.3. Sentiment Analysis

Finally, to complement the quantitative findings, a qualitative assessment of the respondents' feelings about AI in Education was done through a *Sentiment Analysis*. Also known as opinion mining, Sentiment Analysis (SA) is the computational study of people's emotions, opinions, and sentiments toward a certain topic or entity, such as organizations, products, services, or individuals (Medhat et al., 2014). The field has gained an important role since 2000, being one of the most active research areas in natural language processing (NLP). In recent years, it has spread from computer science to social sciences, with a growing relevance to fields like marketing, finance, political science, and communications, due to the importance of people's beliefs and perceptions in decision-making processes (Hussein, 2018). To conduct the sentiment analysis and show the necessary plots, the R language was used (with RStudio), along with the following packages: *tidyverse*, *syuzhet*, and *tidytext*.

As far as data set collection procedures are concerned, all three analyses were based on the same online survey (more information in the *Sample Description* section below). However, the information was taken from different parts of it. For the descriptive and analytical statistical analysis, data were retrieved from the sociodemographic questions at the end of the questionnaire and the section designated for knowledge of AI in education. In turn, the SEM-PLS analysis used information from the sections *benefits*, *barriers,* and *knowledge* of AIEd. Finally, one question was reserved for the sentiment analysis: "Please write 3-5 words about how the implementation of AI in Portuguese schools makes you feel". The figure below summarizes the investigation model of the thesis.

Figure 5.2 – Integrated investigation process



Source: Author's elaboration

5.3. Sample Description

A questionnaire was conducted for teachers in Portuguese primary and secondary schools (6-18 years range) to evaluate their perceptions of the implementation of AI in Education. Since the aim of this dissertation focuses on non-higher education, university teachers were excluded. This survey is based on non-probability convenience sampling — resulting in the availability and accessibility of the individuals addressed — and was disseminated through online channels such as social networks (e.g., Facebook, Instagram, WhatsApp) and online groups.

For two weeks (July 2022), a total of 419 responses were obtained, of which 184 were usable. It was considered as exclusion criteria all participants who did not complete the questionnaire. Although the satisfactory response rate (44%; n=419), the conclusions of this research should be carefully viewed, considering the small sample size. This factor presents itself as the main limitation of this study, although the primary purpose of this survey was not to obtain a sampling frame for the target population.

When analyzing the gender distribution, 84% of the teachers surveyed identified themselves as female, while 16% identified as male. Concerning age ranges, most respondents are between 40-49 years old (45%), followed by those aged 50-59 (33%) and 60 and older (9%). This last group also includes recently retired respondents. The representation of younger teachers is lower (7% for the 20-29 age group and 6% for the 30-39 age group). Regarding academic qualifications, 66% of the respondents have a bachelor's degree, 28% a master's degree, 4% a doctorate, and 1% a high school diploma.

Of the teachers surveyed, 32% teach in the first cycle, 10% in the second cycle, and 23% in the third cycle of basic education, while 34% are secondary or vocational teachers. Furthermore, 79% of the respondents teach in public institutions, while 21% teach in private schools. Concerning the teachers' subject area, the mode is in Languages and Social Studies (34%), whereas 27% teach math and science subjects, 9% physical education, 7% art and technology subjects, and 1% moral and religious education. Of the 22% who answered 'other,' most teach in primary school (mono-grade teaching), and a few identified special education and specific subjects in vocational courses. The present categorization follows the current curricular framework of the Portuguese educational system, established by the Directorate-General of Education of the Portuguese Republic in the Decree-Law of July 5, 2012. For a summarized view of the sample distribution, it is suggested to consult appendix B. Regarding the geolocation, all the respondents live in Portugal, and are distributed as follows in Annex A.

Chapter VI — Results Presentation and Discussion

6.1. Descriptive and Analytic Statistics Analyses

6.1.1. Results Presentation

The present section aims to answer the investigation's research question (*what is the possibility of implementing AI in Portuguese schools?*) with focus on the hypothesis 'Sociodemographic differences influence knowledge of AIEd'. Using a seven-point Likert scale (Likert, 1932), descriptive and analytic statistics analyses were conducted with the aim to investigate possible linkages between sociodemographic factors and respondents' knowledge of AI in education. Regarding data collection procedures, the information was retrieved from the online questionnaire that supports this thesis, namely from the sections related to the knowledge of AI and sociodemographic questions.

Following the approach proposed by Baker et al. (2019), knowledge of AIEd can be analyzed from three dimensions: knowledge *about*, *with* (using AI technologies), and *for* AI (a world shaped by AI). Simple descriptive statistics analysis was first conducted considering these three categories, as can be seen in the table below. The results include the sample mean ($\bar{X}$), median, standard deviation, minimum and maximum values, excess kurtosis, and skewness for each respective survey indicator.

Table 6.1. – Descriptive Statistics about knowledge of AI

Knowledge		Mean	STDev	Median	Mode	Min-Max	Kurtosis	Skewness
About AI	I know what AI is.	5,176	1,413	5	5	1-7	0,910	-0,857
	I am familiar with concepts inherent to AI such as ML.	4,139	1,720	4	5	1-7	-0,662	-0,419
	I am familiar with concepts inherent to AI such as LA.	3,441	1,859	3	1	1-7	-1,188	0,091
With AI	I am aware of how AI is being implemented in educational settings.	3,773	1,926	4	5	1-7	-1,195	-0,061
	IT tools are used in the classroom.	4,266	1,804	5	5	1-7	-0,859	-0,350
	I can program AI.	2,180	1,662	1	1	1-7	0,252	1,208
For AI	I believe in the potential of AI in society at large.	5,219	1,490	5	6	1-7	0,081	-0,721
	I think it is beneficial to implement intelligent systems in schools.	5,300	1,487	5	5	1-7	0,396	-0,834

Source: Author's elaboration

Based on the results, it is possible to observe that the respondents are knowledgeable about AI, with a mean, median, and mode of 5 (max=7). The distribution is negative asymmetric leptokurtic (considering the skewness and excess of kurtosis), meaning that many observations are concentrated near central values (in this case, 5) and in the extreme left of the distribution (close to 1 = 'Totally disagree'). When asked about concepts such as ML or LA, respondents showed to be less knowledgeable, especially concerning the last one. In both cases, there is a greater disparity in the observations (platykurtic distributions). However, while in the 'Knowledge about ML' the observations tend to 'agree,' concerning the "Knowledge about LA", the trend is to 'disagree'.

Moving on to the dimension of knowledge *with* AI, the results inherent to 'I am aware of how AI is being implemented in educational settings' show a greater disparity in observations (considering the values of standard deviation, kurtosis, and skewness). This justifies the lower mean (3,773) in comparison to the values of the median and the mode (4 and 5, respectively). The same is true for the statement, 'IT tools are used in the classroom.' Although the median and mode are 5, the distribution is slightly skewed towards 'agree,' with more observations spread across the distribution, thus influencing the mean. Regarding 'I can program AI,' most observations tend to disagree, with a higher incidence in 1= 'Totally disagree'. Observations between 4 and 7 represent 21% of the sample.

Finally, regarding the last category, a slight tendency to agree is observable among respondents when asked about the potential of AI in both society and schools. In both statements, the median and mean are close to 5 although extreme cases influence the distributions in the left tails of the distributions.

To analyze the internal differences related to these questions, an ANOVA test was used considering seven sociodemographic factors: *school cycle* (where respondents teach), *age*, *gender*, *educational level*, *teaching area*, *sector* (public/private), and *region*[4]. The full results tables are presented in tables 8.2. to 8.8. in Annex D. For the sake of clarity, the table below brings together only the indicators that show statistically significant differences (p-value < 0.05). Note that none were found between factors such as *school cycle*, *sector*, or *region*.

Table 6.2. – ANOVA tests for knowledge of AI (significant results only)

Knowledge of AI ~		Groups	Sum of Squares	Degrees of freedom	Mean Square	F value	p-value
Age	I am familiar with concepts inherent to AI such as ML.	Between Groups	34,864	4	8,716	3,104	,017
		Within Groups	474,544	169	2,808		
Gender	I know what AI is.	Between Groups	15,884	1	15,884	8,223	,005
		Within Groups	332,231	172	1,932		

[4] Divided by NUTS II, accordingly to the common classification of territorial units for statistics.

Gender	I think it is beneficial to implement intelligent systems in schools.	Between Groups	17,265	1	17,265	8,301	,004
		Within Groups	357,729	172	2,080		
Education level	I am familiar with concepts inherent to AI such as LA.	Between Groups	27,843	2	13,921	4,156	,017
		Within Groups	572,830	171	3,350		
Teaching area	I am aware of how AI technologies are being implemented in educational settings.	Between Groups	52,030	4	13,007	3,712	,006
		Within Groups	592,229	169	3,504		

Source: Author's elaboration

Since the ANOVA test only identifies internal discrepancies between groups but does not specify them, the Tukey's HSD pairwise test was used. This post hoc ANOVA statistical test is helpful for finding means that are significantly different from each other. Table 6.3 shows the results of the Tukey's test for the list of factors above, as well as the lower and upper confidence interval values, the difference of the means between each group sample being tested, and the adjusted p-value.

Table 6.3.– Tukey's test for the differences among age, educational level, and teaching area (significant results)

Knowledge of AI ~		**Groups showing significant results**	**Mean difference**	**Lower CI**	**Upper CI**	**p-value adjusted**
Age	I am familiar with concepts inherent to AI such as ML.	30-39 ~ More or equal to 60	-2,362*	-4,23	-,50	,005
Education level	I am familiar with concepts inherent to AI such as LA.	Bachelor's ~ Master's degree	-,889*	-1,62	-,16	,013
Teaching area	I am aware of how AI technologies are being implemented in educational settings.	Languages & Social Studies ~ Other	-1,136*	-2,20	-,07	,031
		Physical Education ~ Other	-1,829*	-3,37	-,29	,011

Source: Author's elaboration

As observed in tables 6.2. and 6.3., there are statistically significant differences between sociodemographic factors like *age*, *gender*, *education level,* and *teaching area*. Starting with *age* ranges, discrepancies were found in the means of two groups – between 30-39 and 60 or older – in relation to the 'respondents' familiarity with concepts such as Machine Learning (ML)'.

Concerning the factor *gender*, the mean difference is significant at the 0.05 level between male and female respondents regarding the statements 'I know what Artificial Intelligence (AI) is' and 'I think it is beneficial to implement intelligent systems in schools.' Note that the *gender* factor is not included in the Tukey's table, as there are only two groups being compared (M/F).

Regarding *education level*, it can be noted that significant differences exist between respondents with bachelor's degrees and respondents with master's degrees when asked about their 'familiarity with concepts such as Learning Analytics (LA)'.

Lastly, in regard to respondents' awareness of how AI technologies are being implemented in educational settings, statistically significant differences were found between subject areas. In particular, between respondents teaching Languages & Social Studies' and teaching in other areas (primarily mono-grade teaching); and among Physical Education teachers and respondents teaching in other areas (primarily mono-grade teaching).

6.1.2. Results Discussion

The literature review began by addressing why the topic of AI in education matters. From here a number of factors were identified — both positive and negative — whose effects must be considered in order to understand the impact of these technologies on the sector. But how can AI be integrated sustainably into the educational landscape? Within the various proposed solutions, from government support to coordinated policy guidance, authors such as Baker et al. (2019) have stressed that actions must also be taken in smaller universes, for example, by increasing knowledge about, with, and for AI. In line with evidence that show that digital literacy can vary significantly as a function of sociodemographic and economic aspects, descriptive and analytical statistical analyses were conducted to determine whether the respondents' knowledge and perception are affected by these factors and to what extent (Chetty et al., 2018; Haenlein & Kaplan, 2019).

The results revealed that the respondents' knowledge *for* AI is slightly higher, followed by knowledge *about* and *with* AI. This leads to the assumption that respondents are (on average) more confident with implementing AI in schools in theory than in practice — thus backing the literature that despite the growing recognition that AI can improve some educational problems, the lack of knowledge still holds schools and teachers back from implementing it (Luckin et al., 2022a). Similarly, this reflects what Renz & Hilbig (2020) and Ferguson & Clow (2017) stressed that the general lack of knowledge about AI and its related concepts (namely LA) results in little evaluation of commercially available tools. Indeed, the statements that showed the lowest scores and the largest deviations were related to teachers' knowledge about ML and LA ($\bar{X}$=4,139; s=1,720 and $\bar{X}$ =3,441; s=1,859, respectively); to their awareness of how AI is being used in education ($\bar{X}$ =3. 773; s=1.926); their capability to program AI ($\bar{X}$=2,180; s=1,662); and whether they use ICT tools in the classroom ($\bar{X}$ =4,266; s= 1,804).

In order to expand the analysis, an ANOVA test was performed to assess whether there were statistically significant differences between different sociodemographic factors. The following factors were considered: *school teaching cycle*, *age*, *gender*, *respondents' educational level, teaching area*, *sector* (public/private), and *region.*

For the dimension' knowledge *about* AI, the results pointed to statistically significant differences between *ages*, *genders*, *education levels,* and *teaching areas*. To better understand these differences, the Tukey's HSD test was performed. Significant results were found in *age* — between 36-50 and 18-25 years, and between 36-50 and 26-35 years — and related to the question 'I am familiar with AI concepts such as Machine Learning (ML).' Considering the factor *gender*, the mean difference was significant for the statement 'I know what Artificial Intelligence (AI) is', while for the *education level* factor, 'familiarity with AI concepts such as ML' was statistically different between respondents with a bachelor's and a master's degree. It is interesting to analyze that, in the specific context of this sample, differences are mainly related to individual characteristics rather than contextual factors such as the education sector or the region. This may suggest that AI in the Portuguese school context is still in an experimental phase. Therefore, risks such as an increase in the gap between public and private education or the uneven development of schools in different regions are not, in light of this sample, evident.

Regarding the dimension' knowledge *with* AI, descriptive statistics revealed that (on average) respondents were not that aware of how to implement AI in practical terms. Once again, the idea that there is a critical gap between what AIEd technologies could do and how they are actually implemented (Baker et al., 2019) prevails. The high standard deviation would lead to believe that significant differences would exist between different sociodemographic groups. However, when ANOVA tests were performed, none proved to be statistically significant. These findings may be biased by the very nature of this sample: all the teachers surveyed share the same cultural background and follow the directions regulated by the same entity (i.e., the state through the Ministry of Education). It may be pertinent to examine this issue further, and under a macro lens in future studies — not least because the size of this sample does not allow conclusions to be drawn.

Lastly, concerning the respondents' knowledge *for* AI, the ANOVA test's p-value revealed to be statistically significant for *gender* and *teaching area*. Interestingly, if internal discrepancies between genders were identified with respect to the statement 'I know what AI is,' the same happened for 'I think it is beneficial to implement intelligent systems in schools.' This may suggest a correlation between these indicators, and an in-depth analysis is suggested for future studies. Regarding *teaching areas*, and since it is constituted by more than two groups, the Tukey's HSD test was then performed to ascertain eventual differences. The means were statistically different between Language & Social Studies teachers ~ teachers of other subjects (such as mono teaching) and Physical Education teachers ~ teachers of other subjects in relation to the statement 'believe in the potential of AI in society at large.'

6.2. SEM-PLS Analysis

6.2.1. Results Presentation

The previous analyses presented an exploratory approach that allowed a deeper comprehension of the respondents' overall knowledge of AIEd. However, it is in the current subchapter that the major hypotheses related to the RQ are tested. Through a quantitative SEM-PLS approach, this analysis aims to understand the effect of the perceived benefits, barriers, and knowledge of AIEd on teachers' intention to implement AI in schools. Data were retrieved from the pages related to these factors from the online survey [Annex C] and evaluated by the respondents through the same seven-point Likert scale.

According to Sarstedt et al. (2017), the examination and interpretation of SEM-PLS results is done in a two-stage process: first, the assessment of the measurement model (i.e., the reliability and validity of the measurement model), and then the structural model.

6.2.1.1. Evaluation of the reliability and validity of the measurement model

In order to assess the reliability and validity of the measurement model, three aspects were taken into consideration: (1) the individual indicators loadings reliability, (2) the convergent validity, (3) internal consistency reliability, and (4) discriminant validity (Sarstedt et al., 2017). Starting with the examination of the indicator loadings:

The results showed that all the 13 indicator loadings related to the Benefits of AI were considered reliable, as all items were above 0,6 and significant when $p < 0{,}001$. According to Sarstedt et al. (2017), this demonstrates that the construct explains more than 50% of the indicator's variance, indicating that the indicator has a satisfactory degree of item reliability. The results can be seen in table 6.4.

Of the 14 indicators related to Barriers of AI, only six standardized factor loadings were above 0,6, which led to the elimination of those that did not meet this statistical criterion (Sarstedt et al., 2017). Despite the unsatisfactory reliability of the individual indicator 10 *The lack of accountability with data* (0,530), it was maintained due to its contribution to the integrity of the model [5].

Lastly, regarding the eight indicators related to the latent variable Knowledge of AI, only two presented an acceptable degree of item reliability (i.e., higher than 0,6). After several tests calculating the PLS algorithm, it was unanimously decided (under the guidance of this thesis' supervisors) that it would be more enriching to analyze a model with more indicators that narrowly miss the measurement model's evaluation criteria than to have only two explaining a latent variable. Therefore, to maintain the

[5] To evaluate the SEM-PLS results, this dissertation follows the composite confirmation analysis steps recommended by Sarstedt et al. (2017). As stated by the authors, the presented steps serve as a guideline for assessing PLS-SEM results and may vary depending on the research context.

integrity of the model, three indicators that did not met this criterion were kept — namely, *Knowledge about ML* (0,494), *Knowledge about LA* (0,427), and *Awareness of the use of AI in Education* (0,515).

Proceeding to the assessment of the constructs' internal consistency reliability, all the constructs presented good reliability levels — with the Cronbach's Alpha (α) and Composite Reliability (CR) values of the constructs exceeding the minimum value of 0,7 (see table 6.4).

Table 6.4 – SEM-PLS Measurement Model Evaluation

Latent Variables	α	CR	AVE	1	2	3	4
Benefits of AI	0,943	0,948	0,593	**0,770**	0,542	0,484	0,682
Barriers of AI	0,870	0,896	0,565	-0,503	**0,752**	0,255	0,321
Knowledge of AI	0,772	0,787	0,447	0,580	-0,273	**0,669**	0,624
Possibility to implement AI	1,000	1,000	1,000	0,675	-0,320	0,743	**1,000**

Note: CR – composite reliability; AVE – average variance extracted. The numbers in bold represent the square roots of the AVE. Below the diagonal elements are the correlations between the constructs. Above the diagonal elements are the HTMT values.

To validate the convergent validity, AVE values must be greater or equal to 0,5, which was the case for all variables except for the latent variable 'Knowledge of AI' (Sarstedt et al., 2017). These values indicate how much the construct explains (on average) the variance of its items. In this case, the benefits and barriers are slightly more reliable than the variable 'Knowledge of AI', explaining more than 50% of the alternative measure's variance.

Lastly, to assess the discriminant validity (i.e., if a construct is empirically distinct from the others), two criteria should be met. First, according to Fornell and Larcker's criterion, the square root of each construct's AVE must be greater than the biggest correlation with the other constructs (Fornell & Larcker, 1981; Sarstedt et al., 2017). Although quite close, the variable 'Knowledge of AI' was the only one that did not satisfy this criterion. Secondly, to assess how distinctly the indicators represent each construct, the Heterotrait-monotrait Ratio (HTMT) criterion was used. This criterion states that all HTMT values must be below 0,85, which was true for all variables.

6.2.1.2. Evaluation of the reliability and validity of the structural model

After satisfactory evaluation of the quality of the measurement model, the conditions were met to analyze the significance of the model's structural relationships and its explanatory and predictive power.

To assess the SEM-PLS structural model, the VIF values were first checked to confirm the absence of collinearity. This criterion was confirmed as all numbers were below the critical value of 5. Once met this condition, the predicative accuracy and relevance of the model were tested. As stated by Sarstedt et al. (2017), to prove predictive accuracy, the coefficient of determination (R^2) values of the two endogenous variables of the model needed to surpass the 10% minimum value. This was confirmed as

Knowledge of AI = 0,337 and the *Possibility of Implementing AI* = 0,642. The predictive relevance of the model was also confirmed by using Stone-Geisser's (Q2) criterion — the two endogenous variables were greater than 0 (showing a value of 0,116 and 0,606, respectively).

Skipping to the next step, bootstrapping procedure on SmartPLS was conducted to assess direct and indirect effects between constructs. Starting with the direct effects showed in table 6.5, the *Benefits of AIED* have a significant positive effect on the *Knowledge of AI* (β=0,599 when p<0,001) and on the *Possibility of implementing AI in Portuguese schools* (β=0,372; p<0,001), holding the hypothesis H1a and H1b. Hypothesis H3a was also confirmed, as the Path Coefficient (β) = 0,528, and the p-value is statistically significant. No statistical evidence was found to support hypothesis H2a or H2b, as the *Barriers of AIEd* do not show a significant positive effect on the *Knowledge of AI* (β=0,017; p=0,747) nor on the *Possibility of implementing AI in Portuguese Schools* (β=0,009; p=0,804).

Table 6.5 – Direct effects between constructs (SEM-PLS results)

	Path Coefficients	Standard Deviation	T Statistics	p-values
Benefits of AI in Education → Knowledge of AIEd	0,599	0,063	9,402	0,000
Benefits of AI in Education → Possibility of implementing AI in Portuguese K-12 schools	0,372	0,075	4,977	0,000
Barriers of AI in Education → Knowledge of AIEd	0,017	0,081	0,322	0,747
Barriers of AI in Education → Possibility of implementing AI in Portuguese K-12 schools	0,009	0,053	0,249	0,804
Knowledge of AIEd → Possibility of implementing AI in Portuguese schools	0,528	0,067	7,950	0,000

Source: Smart PLS

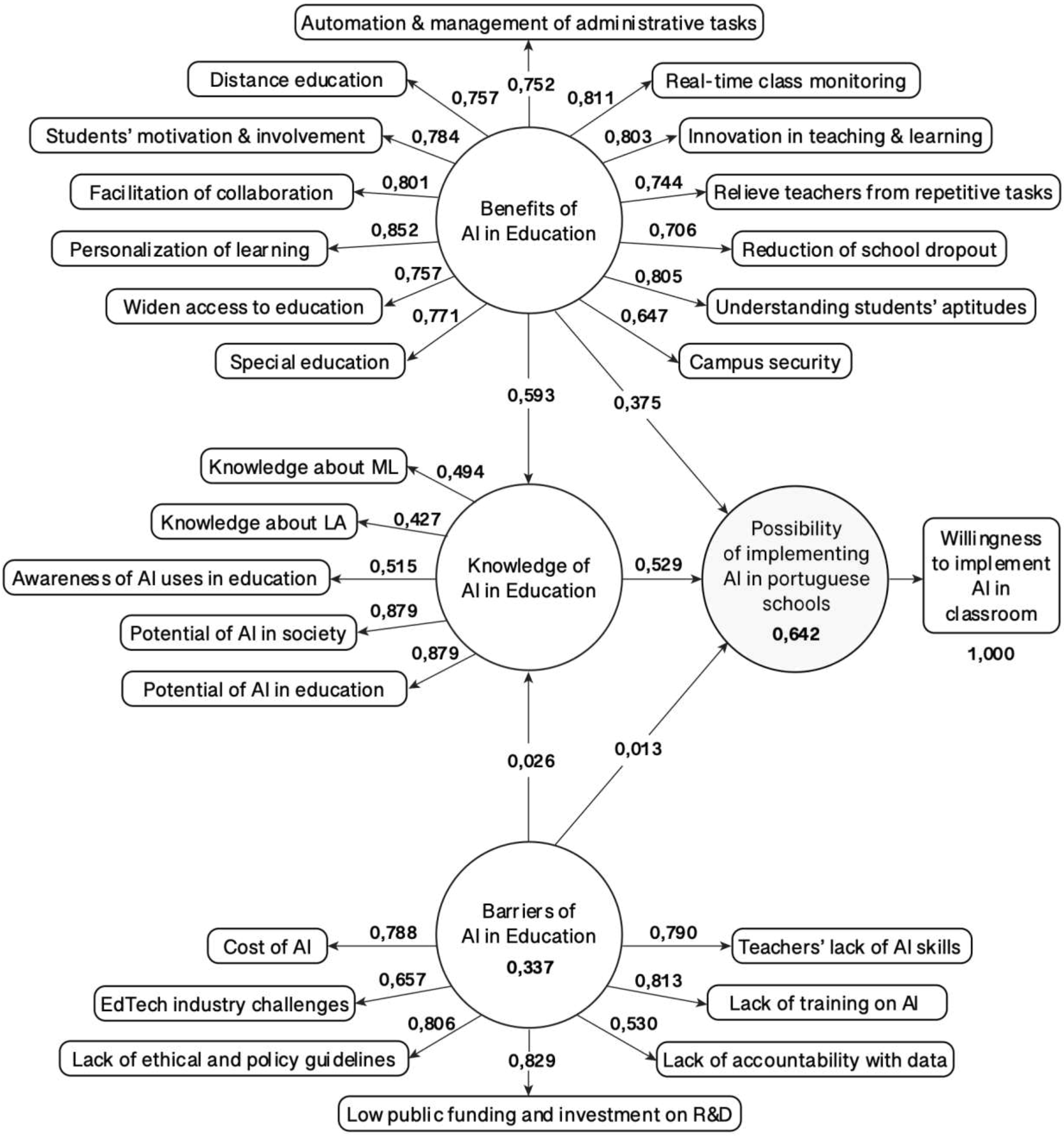
Table 6.6 – Indirect effects between constructs (SEM-PLS results)

	Path coefficients	Standard Deviation	T Statistics	P Values
Benefits of AI in Education → Knowledge of AI → Possibility to implement AI in Portuguese schools	0,316	0,053	5,869	0,000
Barriers of AI in Education → Knowledge of AI → Possibility to implement AI in Portuguese schools	0,009	0,043	0,322	0,747

Source: Smart PLS

Moving to the indirect effects (see table 6.6) it was possible to confirm hypothesis H3b — which states that the Knowledge of AI mediates the effect of Benefits of AI on the possibility of implementing it in Portuguese schools (β=0,316 when p=0,000). In turn, no evidence was found that the *Knowledge of AI* mediates the relationship between the *Barriers of AIEd* and the *Possibility of implementing AI in Portuguese schools* (β=0,009; p=0,747).

Figure 6.1– Conceptual Model Results



Source: SmartPLS

6.2.2. Results Discussion

With the primary aim of assessing this study's research question, i.e*., the possibility of implementing Artificial Intelligence in Education*, it was developed a conceptual model that could quantitively test the research hypotheses. Based on the previous literature review, three variables were identified — *Benefits of AIEd, Barriers of AIED,* and *Knowledge of AI* — along with their respective indicators. To empirically validate whether these latent variables and indicators were relevant to the study, tests were conducted using the software SmartPLS.

Regarding the *Benefits of AIEd*, the results were in line with the literature review, as all indicators proved to be statistically significant for the study (greater than 0.6 when p <0.001). This resulted on a total of 13 indicators contributing for the variable, these being: 1) *Widen access to education* (Miao et. al., 2021; Yao & Yang, 2020); 2) *Personalization of learning* (Renz & Hilbig, 2020); 3) *Students' motivation and involvement* (Hilbig et al., 2019; Tahiru, 2021; Yao & Yang, 2020), 4) *Facilitation of collaboration* (Baker et al., 2019; Feng & Law, 2021); 5) *Distance education* (Yao & Yang, 2020); 6) *Special education* (Drigas & Ioannidou, 2013; Smuha, 2020; Yao & Yang, 2020); 7) *Real-time class monitoring* (Baker et al., 2019; Yao & Yang, 2020); 8) *Understanding students' aptitudes* (Baker et al., 2019; Yao & Yang, 2020); *9) Innovation of teaching and learning practices* (Baker et al., 2019; Smuha, 2020; Miao et. al., 2021); 10) *Relieve teachers from repetitive tasks* (Jules & Salajan, 2019); 11) *Automation and management of administrative tasks* (Jules & Salajan, 2019); 12) *Campus security* (Yao & Yang, 2020); and 13) *Reduction of school dropout* (Smuha, 2020).

As far as Barriers of AI are concerned, only seven indicators proved to have a significant effect on the possible implementation of AI in Portuguese schools, namely: *Low public funding and investment in R&D for AIEd* (Baker et al., 2019), *Lack of ethical and policy guidelines specific to AI in K-12 education* (Roll & Wylie, 2016), the *High cost of AI* (Yao & Yang, 2020), *Teachers' lack of skills on AI* (Hoeschl et al., 2018), *Lack of training on AI* (Baker et al., 2019; Ferguson & Clow, 2017), the *Lower return that AI generates in the education market* (Baker et al., 2019), and *Lack of accountability with data* (Baker et al., 2019; Tahiru, 2021). In turn, the ones that did not contribute to the analysis were removed. The results revealed that most indicators related to data-specific issues — i.e., *Data privacy and security breaches* (Baker et al., 2019; Yao & Yang, 2020), *Difficult access to data* (Roll et al., 2021), *Distortions in data and results* (Baker et al., 2019) — were not significant for the analysis, which may be partially explained by the still relatively low levels of knowledge about AI and its paradigms (Ayanwale et al., 2022; Baker et al., 2019; Ferguson, 2012; Renz & Hilbig, 2020). The indicators related to the *Reduced scientific evidence on AIEd* (Baker et al., 2019) and the *Little development of AI-based solutions from Edtech companies* (Tahiru, 2021) also proved not significant for the model. In line with the literature review, this may be justified by the lack of collaboration between key stakeholders such as EdTech companies, schools, researchers, teachers, etc. (Baker et al., 2019).

Regarding the *Knowledge of AI*, the results show that the indicators with the highest score of individual reliability were related to the dimension 'Knowledge *for* AI' — namely, I *believe in the overall potential of AI in society, and* I *believe that AI is beneficial for schools* (both scoring 0,879 when p <0,001). This led to the removal of the indicators that did not meet the individual validity criterion, with the exception of *I am familiar with AI concepts such as Machine Learning* (Baker et al., 2019), *I am familiar with concepts inherent to AI such as Learning Analytics* (Baker et al., 2019), and *I am aware of how AI technologies are being implemented in educational settings* (Baker et al., 2019), due to model integrity reasons. These findings corroborate the results of the previous analysis, as the individual factors that seem to contribute most to the implementation of AI in schools are related to a general belief in the potential of AI. Apparently, and although the reliability of the individual loadings of the last three indicators is not as substantive, they have been shown to contribute to the overall model, thus supporting the literature that practical knowledge about AI and concepts such as ML LA are also important for efficient implementation of AI in k-12 schools (Bates et al., 2020; Kabudi et al., 2021; Luckin et al., 2022; Renz & Hilbig, 2020).

Finally, for the dependent variable, 'Possibility of implementing Artificial Intelligent technologies in Portuguese primary and secondary schools,' a final indicator was added to understand teachers' willingness to use AI in their classes. Having identified the three main factors which may impact the implementation of AI in Portuguese schools, the hypotheses of this study were tested.

Starting with the direct effects of the conceptual model, the results showed that the *Benefits of AIED* have a significant positive impact both on the *Knowledge of AI* and the *Possibility to Implement AI in Portuguese schools*, thus confirming hypotheses H1a and H1b. According to the literature, this may reflect the growing presence of the "techno-solutionist" paradigm in educational discourses, emphasizing the revolutionary role of emerging technologies such as AI while downplaying its risks (Neves & Holmes, 2020). Indeed, when evaluating the direct effects of the Barriers of AI on the Knowledge of AI and on the Possibility of implementing it in schools, no statistical evidence was found, which led to infirming the hypotheses H2a and H2b. The third direct effect tested in the model was related to hypothesis H3a, which states that Knowledge of AI positively impacts the possibility of implementing AI in Portuguese primary and secondary schools. In line with the literature, this hypothesis was then confirmed, as the p-value was equal to 0,000 for a significant value of 0,05.

Regarding indirect effects, hypotheses H4a and H4b were analyzed based on the mediating factor of Knowledge of AI. These hypotheses aimed to assess respectively the impact of the Benefits and Barriers of AIEd on the intention to implement AI in Portuguese schools through the mediating factor knowledge of AI. Once again, the results confirmed that the knowledge associated with the Benefits of AIEd shows a significant influence on the possibility of implementation, thus confirming hypothesis H4a. In turn, the knowledge related to the Barriers of AIEd did not show significant evidence to prove hypothesis H4b, which can be justified by the reduced knowledge about AI and its paradigms (Baker et al., 2019; Ferguson, 2012) or by the already mentioned general belief that technology can solve the most complex problems in education (Neves & Holmes, 2020).

6.3. Sentiment analysis

6.3.1. Results Presentation

Lastly, a Sentiment Analysis (SA) was conducted to assess the respondents' feelings toward implementing AI in Portuguese primary and secondary schools. The process of SA follows a sequence of steps that includes collecting, pre-processing, and cleaning the input data that will later be categorized into sentiments and represented graphically (Hussein, 2018).

Starting with data collection, the inputted data were extracted from the same questionnaire that supported the previous quantitative analyses. However, for this specific case, one question was designated for the analysis: "Please write 5-10 words that come to mind when you think of Artificial Intelligence in education". Although this question was marked as mandatory (just as other survey questions) because it was open-ended, not all respondents submitted their words. This led to a reduction of the dataset to 146 responses — although it can be considered a limitation of this study, it did not limit the significance or representativeness of the results.

The second stage involved text pre-processing. Due to the scarcity of linguistic resources available for the Portuguese language (Madhoushi et al., 2015; Tavares et al., 2021), data were converted to English. To overcome this limitation, the answers were translated manually with the help of the translator DeepL, trying to mitigate any possible loss of meaning or intent in the translation process. Then, text pre-processing techniques were used to clean the data, using functions to remove punctuation, stop words, lowering words, and the function unnest_tokens(), which creates a dataset with one word per row. In line with Monteiro (2020), these tasks are important in training a model since they reduce time and processing power. Once the data was set, a word cloud was built for data visualization, showing the words with the highest frequency. It was employed the RStudio's *wordcloud* package. As observed in figure 6.2, the words with the highest number of occurrences were 'innovation,' 'future,' 'learning,' 'evolution,' 'technology,' 'motivation,' 'automation,' among others.

Figure 6.2 – Wordcloud with the most frequent words

Source: RStudio

Before proceeding to the sentiment analysis, one last step was considered — defining the criteria for classifying sentiments. Following Monteiro (2020), there are two levels of classifications, as shown in the table below.

Table 6.7 – Classification level and sentiment classification

Classification Level	Sentiment Classification
– *Document Level:* identifies an overall sentiment on a single topic from a document. – *Sentence Level:* identifies a sentiment on each (subjective) sentence of a document. – *Aspect Level:* identifies a sentiment for more than one aspect (document/sentence level). – *Comparative Level:* identifies opinions that instead being direct about a topic, compares it with others.	– *Lexicon-based:* assigns pre-defined sentiments to known terms. The lexicon can be created manually, dictionary-based, or corpus-based (uses a corpus of specific documents to expand an existing set of words). – *Machine Learning*: uses divided into supervised and unsupervised strategies for lexicon creation. – *Hybrid*: combine both methods to reduce the impact of each one's shortcomings.

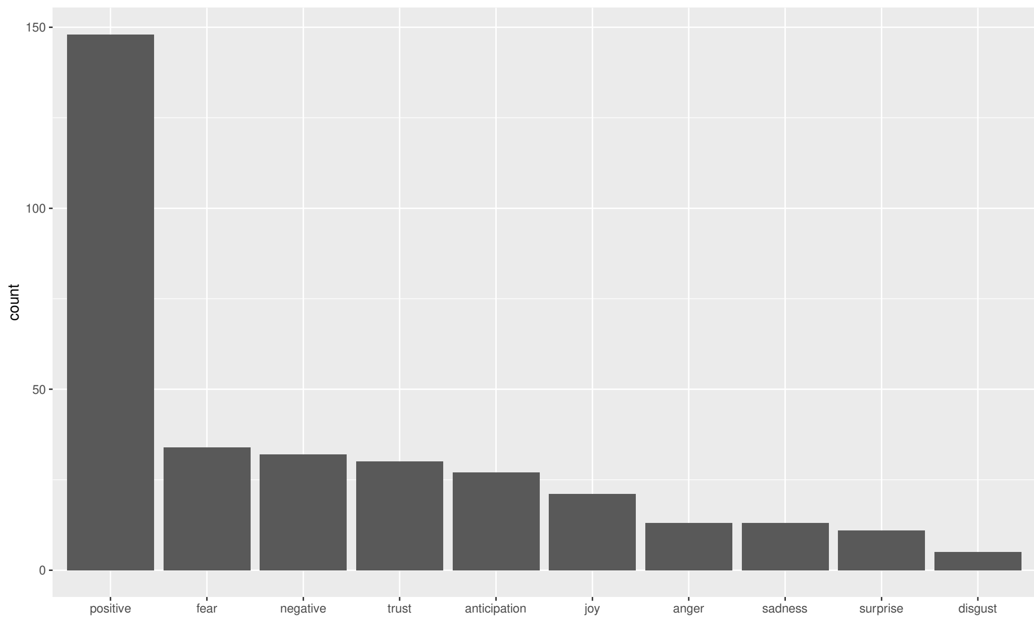
Source: Author's elaboration (adapted from Monteiro, 2020)

For this analysis, a sentence-level lexicon-based approach was adopted, with scores set according to the emotion lexicon dictionaries 'NRC', 'Bing,' and 'Loughran.'

To evaluate the sentiments of the dataset, the NRC emotion lexicon was first called (using the *syuzhet* package), identifying eight basic emotions {anger, anticipation, disgust, fear, joy, sadness, surprise, and trust}, two sentiments {positive, negative}, and their corresponding valence in the dataset. Considering the NRC lexicon, a total of 200 sentiments were found, as shown in table 8.9 in Annex E. The sentiment scores were then sorted in descending order and displayed in the following plot:

Based on this dataset, it is possible to observe that most words represent a positive sentiment, while the main emotions were fear, trust, and anticipation.

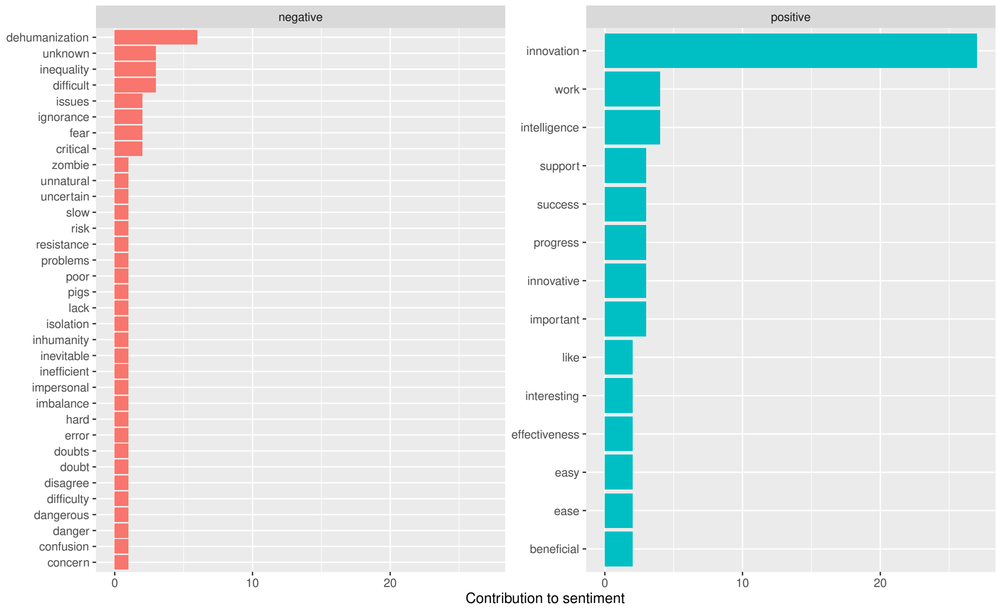
Figure 6.3 – Sentiment Scores about AI in Education (NRC lexicon)



Source: RStudio

For a deeper understanding of the negative and positive sentiments towards the topic of AI in Education, a Bing analysis was carried out using the *tidytext* package. As in the previous analysis, the get_sentiments () function was run, and the sentiments corresponding to each word were defined accordingly to the Bing lexicon. Therefore, 81 words were calculated, and each was assigned a sentiment (as shown in table 8.10 in annex E). Rather than creating a barplot containing all words, only the top 10 words were selected for each sentiment.

Figure 6.4 – Sentiment Scores about AI in Education (Bing lexicon)

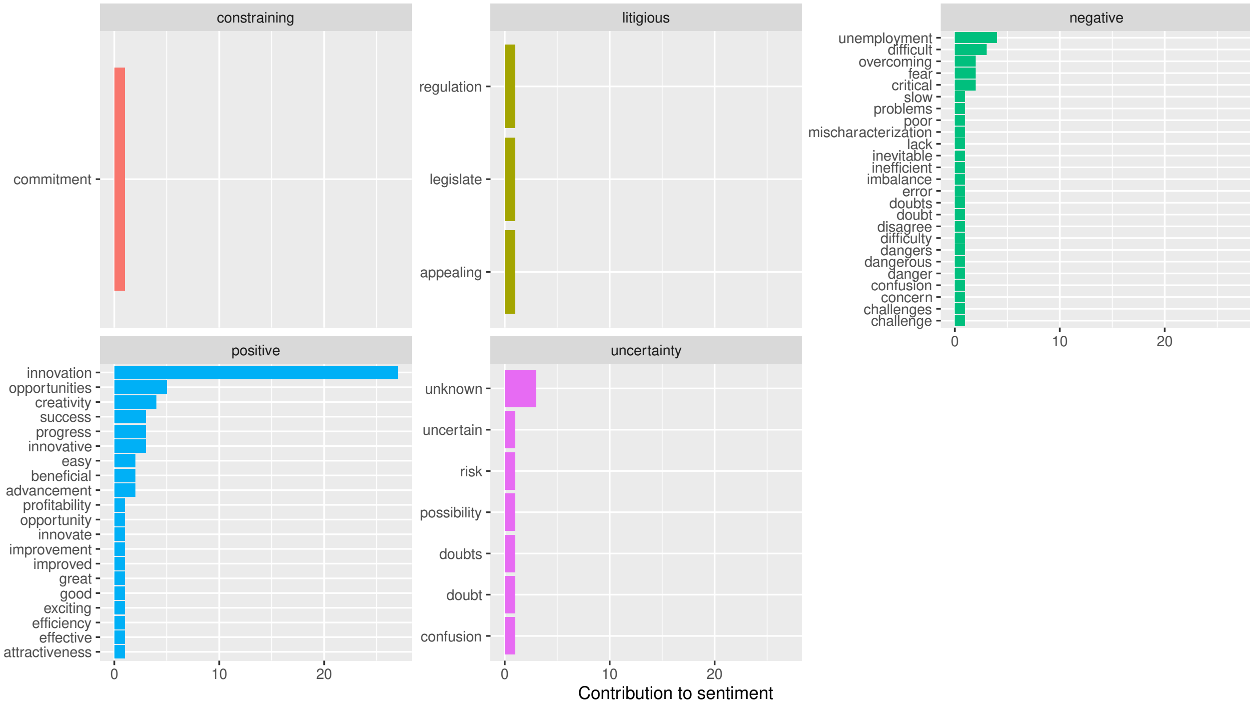


Source: RStudio

As displayed in figure 6.4, the results show that a higher number of words contribute to the positive sentiment, such as: ‘innovation,’ ‘work,’ ‘intelligence,’ ‘support,’ and ‘success.’ In turn, the top five negative words were ‘dehumanization,’ ‘unknown,’ ‘inequality,’ ‘difficult,’ and ‘issues.’

Finally, and since this study is done within the management framework, the English sentiment dictionary ‘Loughran’ was applied. This lexicon labels words with six possible sentiments important in financial contexts: ‘negative’, ‘positive’, ‘litigious’, ‘uncertainty’, ‘constraining’, or ‘superfluous’. These classifications can be found in table 8.11 in Appendix E. Again, word frequency was calculated, and a plot was created. According to this lexicon, the words in the data set mostly corresponded to positive sentiment and, albeit in smaller quantity, to negative and the feeling of uncertainty.

Figure 6.5 – Sentiment Scores about AI in Education (Loughran lexicon)



Source: RStudio

6.3.2. Results Discussion

To complement the results obtained in the quantitative analyses presented before, a sentiment analysis was conducted to evaluate the respondents' feelings toward the possible implementation of AI in Portuguese primary and secondary schools. As mentioned earlier, a specific open-ended question in the survey was addressed to this analysis, asking respondents to write down some words they associate with AI in education. Once tidy the data, the then structured information was analyzed through a lexicon-based classification approach, namely using *NRC*, *Bing*, and *Loughran* lexicons.

In light of the results, the three lexicon dictionaries highlighted that positive feelings are prevalent in the surveyed sample. These findings supported the already tested hypothesis H1a, which states that the Benefits of AIEd contribute to the possibility of implementing AI in Portuguese schools. A closer analysis based on the 'Bing' lexicon sought to understand which words contributed most to this sentiment; 'innovation' was the word with the most weight (and also the most mentioned, according to the word cloud created), followed by 'work,' 'intelligence,' 'support' and 'success.' Also, in the lexicon 'Loughran,' innovation was the most relevant word for the positive sentiment, followed by 'opportunities,' 'creativity,' 'success,' and 'progress.'

Interestingly, the number of words associated with the negative sentiment was much lower compared to the positive sentiment. This may be a result of several factors, among them the relatively low levels of knowledge of AI or the emergent idea that AI may trigger a revolution in the educational landscape (Ayanwale et al., 2022; Mertala et al., 2022).Whether for these or other reasons (including limitations of this study such as the small sample size), let these results serve as clues for future studies.

Chapter VII – Conclusions

7.1. Final Considerations

Artificial Intelligence in Education has opened up opportunities to expand educational practices. From Intelligent Tutoring Systems (ITS) to AI-powered teaching assistants (Baker et al., 2019; Renz & Hilbig, 2020; Pedró et. al, 2019), AI has been increasingly adopted and used in the education sector, particularly in education institutions (Holmes et al., 2019; Pedró et. al, 2019). However, despite the potential to transform education, a *per loco* implementation of these systems would not only not solve the most profound problems in education but could even accentuate them. Therefore, as this is an issue that concerns such a wide range of stakeholders (e.g., students, teachers, programmers, instructional designers, EdTech companies, governments...), research must promote an integrated view that considers both the promises and implications of these systems at the various touchpoints. In this sense, this study's objective was to assess the impact of AI in education, seeking to contribute, both professionally and academically, to a more comprehensive picture of the actual effects of this phenomenon.

Following an extensive literature review on AI and its interconnection with education, data was collected and analyzed from a questionnaire with 184 valid responses from Portuguese teachers. This survey aimed to assess how the respondents perceive the effects of AIEd and how this was reflected in the possibility of implementing these systems in Portuguese primary and secondary schools. Therefore, and in line with the literature, three dimensions were examined: the respondents' perception of the benefits, the barriers of AIEd, and their knowledge about AI and AIEd. Since this study was based on soft data (i.e., knowledge and perceptions), a mix of quantitative and qualitative research approaches were used to enrich the results obtained for this study's research question (*What is the possibility of implementing AI in Portuguese primary and secondary schools?*).

Descriptive and analytic statistics were first conducted to assess the respondents' knowledge of AI in Education according to the three levels of knowledge defined in the literature review — knowledge *about*, *with*, and *for* AIEd (Baker et al., 2019; Holmes et al., 2019). Given that this has been such a widely covered topic in the literature and presented as one of the main factors for successful AI in education, this primary analysis was important to understand the respondents' overall knowledge and hence perceptions (later examined through the SEM-PLS analysis).

The results showed that, in general, there was no statistical confirmation that respondents had a great knowledge *about* AI, especially when asked about related concepts such as Machine Learning or Data Analytics. The findings of this analysis also highlighted that the highest score dimension (around 5.3 on a Likert scale from 1 to 7) was the 'Knowledge for AI.' This confirmed Baker et al. (2019) theory that most respondents recognize the value of AI in society at large and schools, thus being willing to implement these technologies in educational institutions. However, when analyzed the level of knowledge *with* AI, the lowest overall results were obtained and with the greatest discrepancies in responses among the respondents — thus highlighting a critical gap between the potential of AI in theory and practice. To understand whether these discrepancies in the knowledge of AIEd were related to sociodemographic factors, in line with Haenlein & Kaplan (2019) view, analyses of variance tests were conducted.

The greatest statistical differences were found at the level of knowledge *about* AI — with more significant variances between different *teaching cycles*, *age groups*, *genders*, and *education levels*. Regarding the 'knowledge *for* AI,' variance differences were found between *genders* and *teaching areas*. Apparently, these results suggest that the factors that most influence possible discrepancies in the respondents' knowledge about AIEd are related to the teachers' personal experiences rather than external factors such as the geographic location or education sectors (private or public). Considering that the teachers surveyed are part of the same cultural context and follow the same governmental guidelines, some questions remain open: are Portuguese schools equally aware of the implementation of AI, or is this a reflection of the lack of incentives and national policies that effectively allow AI to be applied in schools? Although no conclusions can be drawn from these findings, due to the inherent limitations of this study, we leave these questions open for future studies.

Having made the initial contributions of this empirical analysis, which provided a deeper understanding of the respondents' knowledge about AI and AIEd, a SEM-PLS quantitative approach was used to test this study's hypotheses and answer the research question. As far as can be ascertained, the respondents' perception of the benefits of AIEd seems to positively affect the possibility of implementing AI in Portuguese schools (K-12). In this sense, the results were in line with the theory proposed by the authors studied, as all the benefits identified in the literature review proved to have a significant effect on the respondents' perception. In turn, when analyzing the effect of the barriers of AIEd on this possibility, the same could not be concluded. Some differences were noted:

Firstly, not all of the barriers identified in the literature review proved significant when tested in the conceptual model. In other words, not all of the downsides of AIEd identified in theory actually affect respondents' perceptions. Secondly, and even considering only the barriers that were significant in the perception of the respondents — such as *Low public funding and investment in R&D for AIEd* (Baker et al., 2019), *Lack of ethical and policy guidelines specific to AI in K-12 education* (Roll & Wylie, 2016), the *High cost of AI* (Yao & Yang, 2020), *Teachers' lack of skills on AI* (Hoeschl et al., 2018), *Lack of training on AI* (Baker et al., 2019; Ferguson & Clow, 2017), the *Lower return that AI generates in the education market* (Baker et al., 2019), and *Lack of accountability with data* (Baker et al., 2019; Tahiru, 2021) — there was no statistical evidence to confirm that these were an obstacle to the implementation of AI in Portuguese schools.

Finally, the hypotheses associated with the variable Knowledge about AIEd were tested. The results confirm the theory studied that stresses the importance of this factor, as it proved to influence the possibility of implementing AI in Portuguese schools. However, the results showed that only the perceived benefits significantly affect knowledge about AIED, thus reflecting a willingness to implement these systems. In contrast, there is no evidence that perceived barriers of AIED affect the knowledge of AIED. In light of these results and to confirm whether respondents' perceptions tend to be effectively positive regarding the topic under analysis, the sentiment analysis was used. The questionnaire reserved an open response for this analysis, which asked respondents to write 5-10 words related to their feelings about the topic. Using the natural language processing technique, this analysis confirmed that words associated with positive feelings were prevalent in the sample — namely, 'innovation,' 'work,' 'opportunities, or 'creativity.' Considering that most respondents do not have much experience with AI in practice, are these perceptions influenced by public representations of AI and the narratives surrounding it, as stated by Mertala et al. (2022)?

Although in smaller proportion, the second most recurrent feeling was fear. To some extent, this observation reflects the findings of Renz & Hilbig (2020) that showed that the lack of knowledge in AI is often reflected in people's passive or aggressive attitude towards artificial intelligence. In this particular case, the idea that AI will replace teachers' jobs shows suggests the presence of AI anxiety, as the word that contributes most to the negative sentiment is 'unemployment.' In line with Ayanwale et al. (2022) it is important to understand teachers' feelings, as the behavioral intention can compromise the use of AI in schools.

To summarize, this dissertation intended to show the relationships between the factors that seem to contribute to the implementation of AI in primary and secondary schools (K-12). After an in-depth literature review that allowed to understand the main benefits and implications occurring at the multiple layers and dynamics of the sector, a survey was conducted with primary and secondary school teachers. Hopefully, the results obtained can be valuable resources for those who intend to develop AI-based solutions in education.

7.2. Contribution to the field

Although the field of AI in Education is in itself an interdisciplinary domain that interacts with computer science, AI, education, and social sciences, an increasing number of agents are getting engaged in designing and implementing AI-based solutions in educational contexts (Chen et al., 2020). According to some authors, this trend will shape the forthcoming years of the AIEd field, as an increasing number of interdisciplinary studies is shaping the field (Bozkurt et al., 2021). In particular, and since the introduction of AI in education is mainly promoted by the private sector, it is important that this interdisciplinarity does not compromise the dynamics of the educational field at the expense of the possibilities of Artificial Intelligence. According to Bozkurt et al. (2021), this requires, for instance, consulting experts in education and social sciences with accumulated knowledge of theory and practice in education.

It is upon these assumptions that the present study seeks to contribute to the development of business solutions in the education sector. First, it addresses the relevant and recent state of the art related to Artificial Intelligence and its applications in education. Therefore, it analyzes in depth the main causes affecting the possibility of implementing AI in Portuguese primary and secondary schools. More specifically, this study empirically tests the main benefits and barriers perceived by teachers, in face of their knowledge about AI in education.

7.3. Limitations

In collecting information on the use of AI in Education, it was found that, despite a considerable increase in the number of published studies, there is still little evidence that empirically proves the actual effects of using intelligent technologies in educational settings. Moreover, being this one of the most complex, dense, and heterogeneous sectors of human societies, and AI an intricate and rapidly evolving field of research, there is still much to be investigated. With this in mind, this study presents a small contribution to a field that is still under development.

Concerning the nature of the study, the findings presented in this thesis result from an investigation which is reduced in terms of sample size (considering only teachers from primary and secondary schools), and limited to a specific context (Portugal). For this reason, although this study has reinforced some of the existing theory related to the use of AI in Education, in terms of external validity, the results are not representative or allow generalizations to other contexts or samples.

Finally, as pointed out in the sentiment analysis, the lack of resources available for languages other than English remains a limitation for research in languages such as Portuguese. Furthermore, the approach chosen for the analysis resorted to rule-based natural language processing (NLP) techniques, which, although faster and relatively reliable, may present some classification problems by simply applying rules defined for words, not considering for example the sequence of words in a sentence or how they are combined. In terms of data collection, a larger sample could also have been beneficial in analyzing sociodemographic factors.

7.4. Suggestions for Future Studies

Taking into consideration that some of the limitations mentioned above can be mitigated, this section provides some suggestions that can be considered in future studies. First and foremost, the present study analyzed the impact of AI in K-12 education the Portuguese context, and was attained with convenience sampling. Therefore, the results may not fully represent the population, nor can they be generalized to apply in other contexts without critical reflection. It could be interesting to extend this research approach to other countries, and even to establish possible points of convergence and divergence between educational systems. At the same time, a larger sample could also be beneficial, especially in analyzing sociodemographic factors.

On the other hand, this thesis sought to assess the impact of behavioral factors, namely teachers' knowledge and perception regarding the implementation of AI in educational institutions. It could be interesting to analyze the problem through other factors, such as collaboration between stakeholders, or through different actors, such as students, companies, schools, or researchers — which could ultimately help identifying possible causality relationships between them.

Finally, and because this research fundamentally sought to identify cause-effect relationships between the study variables, the 'why' and 'how' questions raised in the literature review warranted greater focus. However, we believe that the results obtained can open the door for future studies to delve deeper into the practical aspects of the 'what' of AI in education. Of particular interest to the management field, it may be interesting to investigate what kind of tools and solutions can be developed to meet the needs identified in the model of this study.

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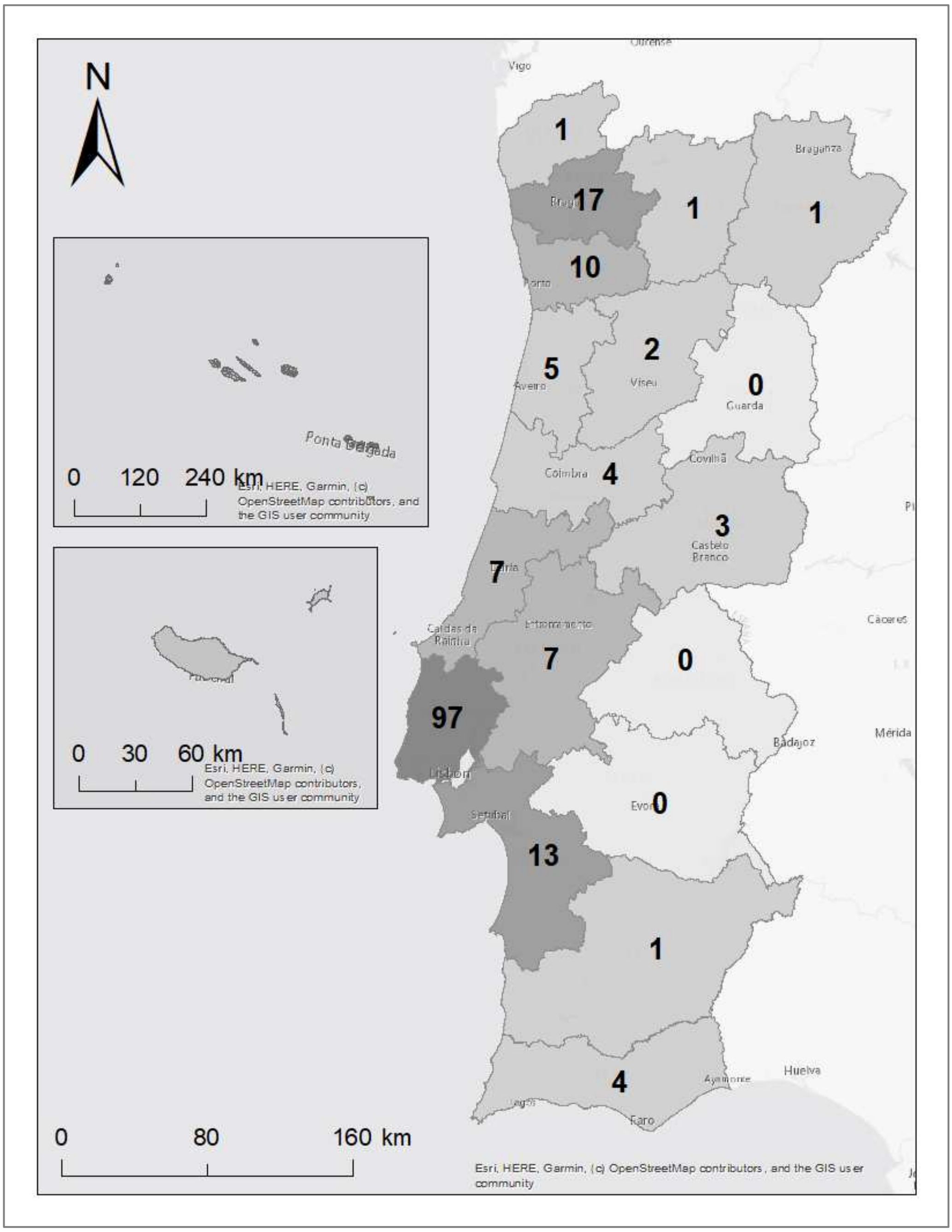
Annexes

Annex A – Geographical distribution of the respondents (Portugal)

Figure 8.1 – Geographical distribution of the respondents (Portugal)



Source: Survey and Directorate General for Territory. Daniel Silva's elaboration

Annex B – Sample categorization by sociodemographic variable

Table 8.1– Sample categorization by sociodemographic variable

Categorization class	Class groups	Percent %
School cycle	1st cycle	31,8
	2nd cycle	10,8
	3rd cycle	23,3
	Secondary/vocational	34,1
Age	20-29	6,8
	30-39	6,3
	40-49	44,9
	50-59	33,0
	60 or more	9,1
Gender	Female	84,7
	Male	15,3
	Non-binary	-
Education level	High School/Professional	0,6
	Bachelor	67
	Master	28,4
	PhD	4
Teaching area	Languages and Social Studies	34,7
	Math and Science	26,7
	Artistic and Technological Education	6,8
	Physical Education	9,1
	Moral and Religious Education	,6
	Other	22,2
Sector	Public	79
	Private	21

Source: Author's elaboration

Annex C – The impact of AI in Education (Online survey)

O IMPACTO DA

Inteligência Artificial na Educação

iscte INSTITUTO UNIVERSITÁRIO DE LISBOA

Intro

Olá!

Sou aluna de mestrado em Gestão de Empresas no ISCTE e estou a desenvolver a minha tese final de mestrado. Gostaria de pedir a sua colaboração neste estudo que visa entender o impacto da Inteligência Artificial (IA) nas escolas portuguesas de ensino básico e secundário (EBS) — do 1º ao 12º ano. **A duração estimada de preenchimento é de 5 minutos**.

Os dados recolhidos serão exclusivamente para fins de investigação científica, cumprindo as condições de anonimato e confidencialidade de todos os participantes. Encontro-me ao dispor para qualquer esclarecimento adicional através do e-mail **amlco2@iscte-iul.pt**.

Obrigada pela sua participação!

Margarida Cardoso

Conceito

Conceito

O que é Inteligência Artificial?

A Inteligência Artificial (IA) é uma área da ciência da computação que procura compreender e construir *sistemas inteligentes* — i.e., máquinas que imitam competências humanas como o raciocínio, a aprendizagem e o comportamento inteligente[1].

A IA está cada vez mais presente em todas as dimensões das nossas vidas: desde as nossas redes sociais (em algoritmos que recomendam conteúdo baseado nos nossos interesses e padrões de consumo); a carros autónomos (i.e., carros que se conduzem a si mesmos), ou até mesmo em medicina, ajudando os médicos, por exemplo, a detetar com antecedência sinais de cancro nos pacientes.

Conceito

O que é Machine Learning?

Os três exemplos acima (redes sociais, carros autónomos e sistemas inteligentes que detetam cancro) recorrem a métodos de Machine Learning.

Machine Learning (ML) é um ramo da Inteligência Artificial que se foca na compreensão e construção de métodos que imitam a *aprendizagem humana*. Por outras palavras, da mesma forma que os humanos aprendem com base nas observações que fazem do mundo, também as máquinas "aprendem" ao encontrar padrões em dados relacionados. Assim, quanto maior o número de dados que uma máquina recebe, mais "inteligente" ela fica.

Isto significa que quantos mais dados tiver, melhor a sua capacidade de fazer associações, de identificar padrões e classificá-los, e de fazer previsões com base naquilo que aprendeu. Tal como o humano, a máquina melhora o seu desempenho até atingir os objetivos e tarefas para as quais foi programada (num processo de constante adaptação e flexibilidade[2]).

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[1] Atkinson, R. (2016). "It's Going to Kill Us!" and Other Myths about the Future of Artificial Intelligence. NCSSS Journal, 21(1), 8–11.

[2] Russell, S., & Norvig, P. (2021). Artificial Intelligence: A Modern Approach (4th Edition).

Em qual destas categorias se insere?

Página 1/6

1. Em qual destas categorias se insere?

- ○ Docente de ensino básico (1º ciclo)
- ○ Docente de ensino básico (2º ciclo)
- ○ Docente de ensino básico (3º ciclo)
- ○ Docente de ensino secundário ou profissional

Página 2/6

2. Conhecimento sobre a IA na Educação

Avalie, item a item, numa escala de 1 a 7, o seu conhecimento sobre a IA na educação:

1 = Discordo totalmente
2 = Discordo bastante
3 = Discordo parcialmente
4 = Não concordo nem discordo
5 = Concordo parcialmente
6 = Concordo bastante
7 = Concordo totalmente
NS/NR = Não sei / Não responde

	1 Discordo totalmente	2	3	4	5	6	7 Concordo totalmente	NS/NR
1. Sei o que é Inteligência Artificial (IA).	○	○	○	○	○	○	○	○
2. Conheço conceitos inerentes à IA tais como Machine Learning (ML).	○	○	○	○	○	○	○	○
3. Conheço conceitos inerentes à IA tais como Learning Analytics (LA).	○	○	○	○	○	○	○	○

	1 Discordo totalmente	2	3	4	5	6	7 Concordo totalmente	NS/NR
4. Estou a par de como as tecnologias de IA estão a ser implementadas em contextos educativos.	○	○	○	○	○	○	○	○
5. Ferramentas de IT são usadas em sala de aula.	○	○	○	○	○	○	○	○
6. Sei programar IA.	○	○	○	○	○	○	○	○
7. Acredito na potencialidade da IA na sociedade em geral.	○	○	○	○	○	○	○	○
8. Vejo como uma mais-valia implementar sistemas inteligentes nas escolas.	○	○	○	○	○	○	○	○
9. Se pudesse implementava sistemas inteligentes na minha atividade educativa.	○	○	○	○	○	○	○	○

Benefícios

Página 3/6

3. Benefícios da Inteligência Artificial (IA) na educação

Classifique, numa escala de 1 a 7, a sua perceção sobre os benefícios que a Inteligência Artificial pode trazer às escolas de ensino básico e secundário (EBS) portuguesas:

1 = Discordo totalmente
2 = Discordo bastante
3 = Discordo parcialmente
4 = Não concordo nem discordo
5 = Concordo parcialmente
6 = Concordo bastante
7 = Concordo totalmente
NS/NR = Não sabe / Não responde

---

	1 Discordo totalmente	2	3	4	5	6	7 Concordo totalmente	NS/NR
1. A Inteligência Artificial (IA) alarga as oportunidades de aprendizagem a um maior número de estudantes.	○	○	○	○	○	○	○	○

	1 Discordo totalmente	2	3	4	5	6	7 Concordo totalmente	NS/NR
2. A IA na educação ajuda a criar percursos de aprendizagem individualizados com base nas características específicas de cada estudante.	○	○	○	○	○	○	○	○
3. A implementação de sistemas inteligentes em contexto escolar ajuda a aumentar a motivação e envolvimento das/dos estudantes.	○	○	○	○	○	○	○	○
4. A IA na educação facilita uma maior colaboração entre estudantes.	○	○	○	○	○	○	○	○
5. A IA facilita o ensino/aprendizagem à distância.	○	○	○	○	○	○	○	○

	1 Discordo totalmente	2	3	4	5	6	7 Concordo totalmente	NS/NR
6. As tecnologias inteligentes podem auxiliar o ensino especial (estudantes com maiores dificuldades de aprendizagem e/ou com incapacidades físicas).	○	○	○	○	○	○	○	○

	1 Discordo totalmente	2	3	4	5	6	7 Concordo totalmente	NS/NR
7. A implementação de tecnologias de IA na sala de aula permite às/aos docentes monitorizar a aprendizagem das/dos estudantes.	○	○	○	○	○	○	○	○
8. As tecnologias de IA ajudam os/as docentes a compreender melhor as aptidões e possíveis lacunas de aprendizagem entre estudantes.	○	○	○	○	○	○	○	○
9. A implementação da IA na educação abre caminho para métodos e abordagens de ensino e de aprendizagem mais inovadores.	○	○	○	○	○	○	○	○
10. A IA ajuda as/os docentes a reduzir o tempo necessário para executar tarefas repetitivas.	○	○	○	○	○	○	○	○

	1 Discordo totalmente	2	3	4	5	6	7 Concordo totalmente	NS/NR
11. A IA facilita a automatização e gestão de tarefas administrativas nas escolas de ensino básico e secundário portuguesas (EBS).	○	○	○	○	○	○	○	○

	1 Discordo totalmente	2	3	4	5	6	7 Concordo totalmente	NS/NR
12. A IA ajuda a reforçar a segurança dentro das escolas portuguesas (EBS).	○	○	○	○	○	○	○	○
13. As tecnologias de IA podem ajudar as escolas a reduzir as taxas de abandono escolar, detetando com antecedência padrões de risco.	○	○	○	○	○	○	○	○

Desafios

Página 4/6

4. Desafios da Inteligência Artificial na educação

Classifique, item a item, numa escala de 1 a 7, a sua perceção sobre os desafios que a Inteligência Artificial pode trazer às escolas de ensino básico e secundário (EBS) portuguesas:

1 = Discordo totalmente
2 = Discordo bastante
3 = Discordo parcialmente
4 = Não concordo nem discordo
5 = Concordo parcialmente
6 = Concordo bastante
7 = Concordo totalmente
NS/NR = Não sei / Não responde

	1 Discordo totalmente	2	3	4	5	6	7 Concordo totalmente	NS/NR
1. A falta de evidência científica sobre o impacto da IA na educação (especialmente no EBS), dificulta a sua integração nas escolas portuguesas (EBS).	○	○	○	○	○	○	○	○
2. O reduzido investimento público em investigação e desenvolvimento de IA na educação, é um obstáculo à implementação da IA nas escolas portuguesas (EBS).	○	○	○	○	○	○	○	○
3. A falta de orientações éticas e políticas específicas sobre a utilização de IA nas escolas, dificulta o uso de sistemas inteligentes nas escolas portuguesas (EBS).	○	○	○	○	○	○	○	○
4. Os custos elevados da implementação, manutenção e utilização de IA na educação, dificultam a implementação de IA nas escolas portuguesas (EBS).	○	○	○	○	○	○	○	○
5. A falta de competências por parte das/dos docentes em IA, afeta negativamente a sua implementação nas escolas portuguesas (EBS).	○	○	○	○	○	○	○	○

	1 Discordo totalmente	2	3	4	5	6	7 Concordo totalmente	NS/NR
6. A falta de mecanismos e de formação específica sobre IA, dificulta a utilização de sistemas inteligentes em contexto de sala de aula.	○	○	○	○	○	○	○	○
7. A maioria das empresas de tecnologias educacionais (EdTech) estão suficientemente desenvolvidas para implementar IA nos seus produtos/serviços.	○	○	○	○	○	○	○	○
8. O menor retorno gerado pela IA no mercado da educação, em comparação com outros, dificulta a integração de IA na educação.	○	○	○	○	○	○	○	○

Riscos

Página 5/6

5. Riscos da Inteligência Artificial na educação

Classifique, item a item, numa escala de 1 a 7, a sua perceção sobre os riscos associados à implementação de Inteligência Artificial nas escolas de ensino básico e secundário (EBS) portuguesas:

1 = Discordo totalmente
2 = Discordo bastante
3 = Discordo parcialmente
4 = Não concordo nem discordo
5 = Concordo parcialmente
6 = Concordo bastante
7 = Concordo totalmente
NS/NR = Não sei / Não responde

---

	1 Discordo totalmente	2	3	4	5	6	7 Concordo Totalmente	NS/NR
1. A implementação de IA na educação acentua desigualdades entre zonas mais desfavorecidas e zonas mais desenvolvidas.	○	○	○	○	○	○	○	○
2. Possíveis violações de segurança e de privacidade de dados dificultam a implementação de IA nas escolas portuguesas (EBS).	○	○	○	○	○	○	○	○
3. A falta de responsabilização com os dados, dificulta a implementação de IA nas escolas portuguesas (EBS).	○	○	○	○	○	○	○	○

	1 Discordo totalmente	2	3	4	5	6	7 Concordo Totalmente	NS/NR
4. O difícil acesso aos dados, prejudica a implementação de IA nas escolas portuguesas (EBS).	○	○	○	○	○	○	○	○
5. Eventuais distorções nos dados e, consequentemente, resultados errados gerados pela IA, dificultam a implementação de IA na escolas portuguesas (EBS).	○	○	○	○	○	○	○	○
6. A possibilidade da IA automatizar tarefas executadas por seres humanos contribui para o aumento do desemprego nas escolas.	○	○	○	○	○	○	○	○
7. O desenvolvimento de IA por agentes não educacionais (ex: empresas) é benéfico para a implementação de IA nas escolas.	○	○	○	○	○	○	○	○

Variáveis Sociodemográficas

Página 6/6

Género

- ○ Masculino
- ○ Feminino
- ○ Não-binário

Idade

- ○ 20-29
- ○ 30-39
- ○ 40-49
- ○ 50-59
- ○ Igual ou superior a 60

Formação escolar

- ○ Ensino Secundário / Profissional
- ○ Licenciatura
- ○ Mestrado
- ○ Doutoramento

Área disciplinar

- Línguas e Estudos Sociais
- Matemática e Ciências
- Educação Artística e Tecnológica
- Educação Física
- Educação Moral e Religiosa
- Outra

Se respondeu outra área, qual?

Tipo de ensino

- Privado
- Público

Código postal (colocar 4 primeiros dígitos)

Por favor escreva 5-10 palavras que lhe ocorrem quando pensa em Inteligência Artificial na educação

Outras sugestões

Powered by Qualtrics

Annex D – ANOVA test results

Table 8.1 – ANOVA test of the Knowledge of AI and the teaching cycle

Knowledge of AI ~ Cycle		**Groups**	**Sum of Squares**	**Degrees Freedom**	**Mean Square**	**F value**	**p-value**
Knowledge About AI	1. I know what Artificial Intelligence (AI) is.	Between Groups	14,820	3	4,940	2,520	,060
		Within Groups	333,295	170	1,961		
	2. I am familiar with AI concepts such as Machine Learning (ML).	Between Groups	13,066	3	4,355	1,492	,219
		Within Groups	496,342	170	2,920		
	3. I am familiar with concepts inherent to AI such as Learning Analytics (LA).	Between Groups	12,469	3	4,156	1,201	,311
		Within Groups	588,204	170	3,460		
Knowledge with AI	4. I am aware of how AI technologies are being implemented in educational settings.	Between Groups	3,388	3	1,129	,300	,826
		Within Groups	640,871	170	3,770		
	5. IT tools are used in the classroom.	Between Groups	3,152	3	1,051	,318	,812
		Within Groups	561,153	170	3,301		
	6. I can program AI.	Between Groups	5,471	3	1,824	,661	,577
		Within Groups	468,696	170	2,757		
Knowledge for AI	7. I believe in the potential of AI in society at large.	Between Groups	4,070	3	1,357	,619	,604
		Within Groups	372,803	170	2,193		
	8. I think it is beneficial to implement intelligent systems in schools.	Between Groups	3,213	3	1,071	,490	,690
		Within Groups	371,781	170	2,187		

Table 8.2 – ANOVA test of the Knowledge of AI and age

Knowledge of AI ~ Age		Groups	Sum of Squares	Degrees Freedom	Mean Square	F value	p-value
Knowledge About AI	1. I know what Artificial Intelligence (AI) is.	Between Groups	11,242	4	2,810	1,410	,233
		Within Groups	336,873	169	1,993		
	2. I am familiar with AI concepts such as Machine Learning (ML).	Between Groups	34,864	4	8,716	3,104	**,017**
		Within Groups	474,544	169	2,808		
	3. I am familiar with concepts inherent to AI such as Learning Analytics (LA).	Between Groups	22,740	4	5,685	1,662	,161
		Within Groups	577,932	169	3,420		
Knowledge with AI	4. I am aware of how AI technologies are being implemented in educational settings.	Between Groups	30,037	4	7,509	2,066	,087
		Within Groups	614,222	169	3,634		
	5. IT tools are used in the classroom.	Between Groups	13,845	4	3,461	1,063	,377
		Within Groups	550,460	169	3,257		
	6. I can program AI.	Between Groups	16,557	4	4,139	1,529	,196
		Within Groups	457,610	169	2,708		
Knowledge for AI	7. I believe in the potential of AI in society at large.	Between Groups	2,861	4	,715	,323	,862
		Within Groups	374,012	169	2,213		
	8. I think it is beneficial to implement intelligent systems in schools.	Between Groups	3,598	4	,899	,409	,802
		Within Groups	371,397	169	2,198		

Table 8.3 – ANOVA test of the Knowledge of AI and gender

Knowledge of AI ~ Gender		**Groups**	**Sum of Squares**	**Degrees Freedom**	**Mean Square**	**F value**	**p-value**
Knowledge About AI	1. I know what Artificial Intelligence (AI) is.	Between Groups	15,884	1	15,884	8,223	**,005**
		Within Groups	332,231	172	1,932		
	2. I am familiar with AI concepts such as Machine Learning (ML).	Between Groups	7,547	1	7,547	2,587	,110
		Within Groups	501,861	172	2,918		
	3. I am familiar with concepts inherent to AI such as Learning Analytics (LA).	Between Groups	3,065	1	3,065	,882	,349
		Within Groups	597,607	172	3,474		
Knowledge with AI	4. I am aware of how AI technologies are being implemented in educational settings.	Between Groups	,185	1	,185	,049	,825
		Within Groups	644,074	172	3,745		
	5. IT tools are used in the classroom.	Between Groups	,073	1	,073	,022	,881
		Within Groups	564,231	172	3,280		
	6. I can program AI.	Between Groups	,537	1	,537	,195	,659
		Within Groups	473,630	172	2,754		
Knowledge for AI	7. I believe in the potential of AI in society at large.	Between Groups	2,928	1	2,928	1,347	,247
		Within Groups	373,946	172	2,174		
	8. I think it is beneficial to implement intelligent systems in schools.	Between Groups	17,265	1	17,265	8,301	**,004**
		Within Groups	357,729	172	2,080		

Table 8.4– ANOVA test of the Knowledge of AI and education level

Knowledge of AI ~ Education level		**Groups**	**Sum of Squares**	**Degrees Freedom**	**Mean Square**	**F value**	**p-value**
Knowledge About AI	1. I know what Artificial Intelligence (AI) is.	Between Groups	3,702	2	1,851	,919	,401
		Within Groups	344,413	171	2,014		
	2. I am familiar with AI concepts such as Machine Learning (ML).	Between Groups	10,978	2	5,489	1,883	,155
		Within Groups	498,430	171	2,915		
	3. I am familiar with concepts inherent to AI such as Learning Analytics (LA).	Between Groups	27,843	2	13,921	4,156	**,017**
		Within Groups	572,830	171	3,350		
Knowledge with AI	4. I am aware of how AI technologies are being implemented in educational settings.	Between Groups	7,011	2	3,505	,941	,392
		Within Groups	637,248	171	3,727		
	5. IT tools are used in the classroom.	Between Groups	1,148	2	,574	,174	,840
		Within Groups	563,157	171	3,293		
	6. I can program AI.	Between Groups	12,805	2	6,403	2,373	,096
		Within Groups	461,362	171	2,698		
Knowledge for AI	7. I believe in the potential of AI in society at large.	Between Groups	,110	2	,055	,025	,975
		Within Groups	376,763	171	2,203		
	8. I think it is beneficial to implement intelligent systems in schools.	Between Groups	3,355	2	1,677	,772	,464
		Within Groups	371,640	171	2,173		

Table 8.5 – ANOVA test of the Knowledge of AI and study field

Knowledge of AI ~ Study field		**Groups**	**Sum of Squares**	**Degrees Freedom**	**Mean Square**	**F value**	**p-value**
Knowledge About AI	1. I know what Artificial Intelligence (AI) is.	Between Groups	5,837	4	1,459	,721	,579
		Within Groups	342,278	169	2,025		
	2. I am familiar with AI concepts such as Machine Learning (ML).	Between Groups	9,131	4	2,283	,771	,545
		Within Groups	500,277	169	2,960		
	3. I am familiar with concepts inherent to AI such as Learning Analytics (LA).	Between Groups	13,666	4	3,417	,984	,418
		Within Groups	587,006	169	3,473		
Knowledge with AI	4. I am aware of how AI technologies are being implemented in educational settings.	Between Groups	52,030	4	13,007	3,712	**,006**
		Within Groups	592,229	169	3,504		
	5. IT tools are used in the classroom.	Between Groups	14,352	4	3,588	1,103	,357
		Within Groups	549,952	169	3,254		
	6. I can program AI.	Between Groups	14,752	4	3,688	1,357	,251
		Within Groups	459,415	169	2,718		
Knowledge for AI	7. I believe in the potential of AI in society at large.	Between Groups	17,320	4	4,330	2,035	,092
		Within Groups	359,553	169	2,128		
	8. I think it is beneficial to implement intelligent systems in schools.	Between Groups	8,719	4	2,180	1,006	,406
		Within Groups	366,275	169	2,167		

Table 8.6– ANOVA test of the Knowledge of AI and education sector

Knowledge of AI ~ Education sector		Groups	Sum of Squares	Degrees Freedom	Mean Square	F value	p-value
Knowledge About AI	1. I know what Artificial Intelligence (AI) is.	Between Groups	6,917	1	6,917	3,487	,064
		Within Groups	341,198	172	1,984		
	2. I am familiar with AI concepts such as Machine Learning (ML).	Between Groups	2,027	1	2,027	,687	,408
		Within Groups	507,381	172	2,950		
	3. I am familiar with concepts inherent to AI such as Learning Analytics (LA).	Between Groups	6,778	1	6,778	1,963	,163
		Within Groups	593,895	172	3,453		
Knowledge with AI	4. I am aware of how AI technologies are being implemented in educational settings.	Between Groups	1,359	1	1,359	,364	,547
		Within Groups	642,899	172	3,738		
	5. IT tools are used in the classroom.	Between Groups	,035	1	,035	,011	,918
		Within Groups	564,270	172	3,281		
	6. I can program AI.	Between Groups	,024	1	,024	,009	,926
		Within Groups	474,143	172	2,757		
Knowledge for AI	7. I believe in the potential of AI in society at large.	Between Groups	3,192	1	3,192	1,469	,227
		Within Groups	373,681	172	2,173		
	8. I think it is beneficial to implement intelligent systems in schools.	Between Groups	,410	1	,410	,188	,665
		Within Groups	374,585	172	2,178		

Table 8.7– ANOVA test of the Knowledge of AI and region (by NUT II)

<table>
<tr><th colspan="2">Knowledge of AI ~ Region (NUT II)</th><th>Groups</th><th>Sum of Squares</th><th>Degrees Freedom</th><th>Mean Square</th><th>F value</th><th>p-value</th></tr>
<tr><td rowspan="6">Knowledge About AI</td><td rowspan="2">1. I know what Artificial Intelligence (AI) is.</td><td>Between Groups</td><td>4,122</td><td>6</td><td>,687</td><td>,333</td><td>,919</td></tr>
<tr><td>Within Groups</td><td>343,993</td><td>167</td><td>2,060</td><td></td><td></td></tr>
<tr><td rowspan="2">2. I am familiar with AI concepts such as Machine Learning (ML).</td><td>Between Groups</td><td>11,799</td><td>6</td><td>1,966</td><td>,660</td><td>,682</td></tr>
<tr><td>Within Groups</td><td>497,609</td><td>167</td><td>2,980</td><td></td><td></td></tr>
<tr><td rowspan="2">3. I am familiar with concepts inherent to AI such as Learning Analytics (LA).</td><td>Between Groups</td><td>4,457</td><td>6</td><td>,743</td><td>,208</td><td>,974</td></tr>
<tr><td>Within Groups</td><td>596,216</td><td>167</td><td>3,570</td><td></td><td></td></tr>
<tr><td rowspan="6">Knowledge with AI</td><td rowspan="2">4. I am aware of how AI technologies are being implemented in educational settings.</td><td>Between Groups</td><td>17,485</td><td>6</td><td>2,914</td><td>,776</td><td>,589</td></tr>
<tr><td>Within Groups</td><td>626,774</td><td>167</td><td>3,753</td><td></td><td></td></tr>
<tr><td rowspan="2">5. IT tools are used in the classroom.</td><td>Between Groups</td><td>27,322</td><td>6</td><td>4,554</td><td>1,416</td><td>,211</td></tr>
<tr><td>Within Groups</td><td>536,982</td><td>167</td><td>3,215</td><td></td><td></td></tr>
<tr><td rowspan="2">6. I can program AI.</td><td>Between Groups</td><td>7,863</td><td>6</td><td>1,310</td><td>,469</td><td>,830</td></tr>
<tr><td>Within Groups</td><td>466,304</td><td>167</td><td>2,792</td><td></td><td></td></tr>
<tr><td rowspan="4">Knowledge for AI</td><td rowspan="2">7. I believe in the potential of AI in society at large.</td><td>Between Groups</td><td>6,565</td><td>6</td><td>1,094</td><td>,493</td><td>,813</td></tr>
<tr><td>Within Groups</td><td>370,308</td><td>167</td><td>2,217</td><td></td><td></td></tr>
<tr><td rowspan="2">8. I think it is beneficial to implement intelligent systems in schools.</td><td>Between Groups</td><td>8,781</td><td>6</td><td>1,463</td><td>,667</td><td>,676</td></tr>
<tr><td>Within Groups</td><td>366,214</td><td>167</td><td>2,193</td><td></td><td></td></tr>
</table>

Annex E – Sentiment analysis by lexicon

Table 8.8 – Word count and sentiment (NRC lexicon)

	Word	Sentiment	n
1	innovation	positive	27
2	learning	positive	17
3	evolution	positive	14
4	technology	positive	12
5	information	positive	5
6	change	fear	4
7	intelligence	fear	4
8	intelligence	joy	4
9	intelligence	positive	4
10	intelligence	trust	4
11	difficult	fear	3
12	important	positive	3
13	important	trust	3
14	inequality	anger	3
15	inequality	fear	3
16	inequality	negative	3
17	inequality	sadness	3
18	interest	positive	3
19	knowledge	positive	3
20	progress	anticipation	3
21	progress	joy	3
22	progress	positive	3
23	success	anticipation	3
24	success	joy	3
25	success	positive	3
26	unknown	anticipation	3

27	unknown	fear	3
28	unknown	negative	3
29	advance	anticipation	2
30	advance	fear	2
31	advance	joy	2
32	advance	positive	2
33	advance	surprise	2
34	advancement	positive	2
35	automatic	trust	2
36	beneficial	positive	2
37	contact	positive	2
38	curiosity	anticipation	2
39	curiosity	positive	2
40	curiosity	surprise	2
41	ease	positive	2
42	fear	anger	2
43	fear	fear	2
44	fear	negative	2
45	ignorance	negative	2
46	intellectual	positive	2
47	interesting	positive	2
48	absolute	positive	1
49	acquire	positive	1
50	adequacy	positive	1
51	administrative	trust	1
52	advanced	positive	1
53	aid	positive	1
54	antisocial	anger	1
55	antisocial	disgust	1
56	antisocial	fear	1

57	antisocial	negative	1
58	antisocial	sadness	1
59	artistic	positive	1
60	attractiveness	positive	1
61	challenge	anger	1
62	challenge	fear	1
63	challenge	negative	1
64	competence	positive	1
65	competence	trust	1
66	complement	anticipation	1
67	complement	joy	1
68	complement	positive	1
69	complement	surprise	1
70	complement	trust	1
71	comprehensive	positive	1
72	confusion	anger	1
73	confusion	fear	1
74	confusion	negative	1
75	constant	positive	1
76	constant	trust	1
77	convenience	positive	1
78	cooperation	positive	1
79	cooperation	trust	1
80	danger	fear	1
81	danger	negative	1
82	danger	sadness	1
83	dangerous	fear	1
84	dangerous	negative	1
85	daring	positive	1
86	develop	anticipation	1

87	develop	positive	1
88	difficulty	anger	1
89	difficulty	fear	1
90	difficulty	negative	1
91	difficulty	sadness	1
92	disagree	anger	1
93	disagree	negative	1
94	discovery	positive	1
95	doubt	fear	1
96	doubt	negative	1
97	doubt	sadness	1
98	doubt	trust	1
99	educational	positive	1
100	educational	trust	1
101	effective	positive	1
102	effective	trust	1
103	efficiency	positive	1
104	engaging	joy	1
105	engaging	positive	1
106	engaging	trust	1
107	error	negative	1
108	error	sadness	1
109	ethical	positive	1
110	exciting	anticipation	1
111	exciting	joy	1
112	exciting	positive	1
113	exciting	surprise	1
114	execution	anger	1
115	execution	fear	1
116	execution	negative	1

117	execution	sadness	1
118	execution	trust	1
119	flexibility	positive	1
120	freedom	joy	1
121	freedom	positive	1
122	freedom	trust	1
123	fundamental	positive	1
124	fundamental	trust	1
125	good	anticipation	1
126	good	joy	1
127	good	positive	1
128	good	surprise	1
129	good	trust	1
130	imitation	negative	1
131	improved	positive	1
132	improvement	joy	1
133	improvement	positive	1
134	improvement	trust	1
135	inefficient	negative	1

Table 8.9 – Word count and sentiment (Bing lexicon)

	Word	Sentiment	n
1	innovation	positive	27
2	dehumanization	negative	6
3	intelligence	positive	4
4	work	positive	4
5	difficult	negative	3
6	important	positive	3
7	inequality	negative	3
8	innovative	positive	3
9	progress	positive	3
10	success	positive	3
11	support	positive	3
12	unknown	negative	3
13	beneficial	positive	2
14	critical	negative	2
15	ease	positive	2
16	easy	positive	2
17	effectiveness	positive	2
18	fear	negative	2
19	ignorance	negative	2
20	interesting	positive	2
21	issues	negative	2
22	like	positive	2
23	advanced	positive	1
24	appealing	positive	1
25	autonomous	positive	1
26	commitment	positive	1
27	complement	positive	1

28	comprehensive	positive	1
29	concern	negative	1
30	confusion	negative	1
31	convenience	positive	1
32	danger	negative	1
33	dangerous	negative	1
34	daring	positive	1
35	difficulty	negative	1
36	disagree	negative	1
37	doubt	negative	1
38	doubts	negative	1
39	effective	positive	1
40	engaging	positive	1
41	error	negative	1
42	ethical	positive	1
43	exciting	positive	1
44	fairness	positive	1
45	fastest	positive	1
46	favor	positive	1
47	flexibility	positive	1
48	freedom	positive	1
49	good	positive	1
50	great	positive	1
51	hard	negative	1
52	imbalance	negative	1
53	impersonal	negative	1
54	improved	positive	1
55	improvement	positive	1
56	individualized	positive	1

57	inefficient	negative	1
58	inevitable	negative	1
59	inhumanity	negative	1
60	intuitive	positive	1
61	isolation	negative	1
62	lack	negative	1
63	personalized	positive	1
64	pigs	negative	1
65	poor	negative	1
66	problems	negative	1
67	pure	positive	1
68	ready	positive	1
69	resistance	negative	1
70	risk	negative	1
71	simplifying	positive	1
72	slow	negative	1
73	super	positive	1
74	sustainability	positive	1
75	triumph	positive	1
76	uncertain	negative	1
77	unnatural	negative	1
78	useful	positive	1
79	well	positive	1
80	wonder	positive	1
81	zombie	negative	1

Table 8.10– Word count and sentiment (Loughran lexicon)

	Word	Sentiment	n
1	innovation	positive	27
2	opportunities	positive	5
3	creativity	positive	4
4	unemployment	negative	4
5	difficult	negative	3
6	innovative	positive	3
7	progress	positive	3
8	success	positive	3
9	unknown	uncertainty	3
10	advancement	positive	2
11	beneficial	positive	2
12	critical	negative	2
13	easy	positive	2
14	fear	negative	2
15	overcoming	negative	2
16	appealing	litigious	1
17	attractiveness	positive	1
18	challenge	negative	1
19	challenges	negative	1
20	commitment	constraining	1
21	concern	negative	1
22	confusion	negative	1
23	confusion	uncertainty	1
24	danger	negative	1
25	dangerous	negative	1
26	dangers	negative	1
27	difficulty	negative	1

28	disagree	negative	1
29	doubt	negative	1
30	doubt	uncertainty	1
31	doubts	negative	1
32	doubts	uncertainty	1
33	effective	positive	1
34	efficiency	positive	1
35	error	negative	1
36	exciting	positive	1
37	good	positive	1
38	great	positive	1
39	imbalance	negative	1
40	improved	positive	1
41	improvement	positive	1
42	inefficient	negative	1
43	inevitable	negative	1
44	innovate	positive	1
45	lack	negative	1
46	legislate	litigious	1
47	mischaracterization	negative	1
48	opportunity	positive	1
49	poor	negative	1
50	possibility	uncertainty	1
51	problems	negative	1
52	profitability	positive	1
53	regulation	litigious	1
54	risk	uncertainty	1
55	slow	negative	1
56	uncertain	uncertainty	1