ARE WE QUICKER TO ALLOW WHAT WE KNOW?

A quantitative study analyzing the correlation between AI literacy, ethical concerns, and stigma on support for AI education in schooling.

JUNE 30, 2025

FIA NASE
S2787733
Supervisor: Wendy Tollenaar

Abstract

Introduction: This paper looks into the various contributions to the different levels of support parents hold towards including AI literacy into standardized educational systems.

Methods: A quantitative survey study (N = 91) was sent out to parents from different countries with children who have at some point in time been in standardized education. The survey measured three independent variables: AI literacy, ethical concerns about AI, and stigma towards AI. The research aimed to discover how these three independent variables influenced the levels of support held by parents towards AI education courses; the dependent fourth variable measured.

Results: The results of this study showed that each independent variable had significant evidence of a correlation to levels of support, with stigma being the most influential. A moderation analysis showed that AI literacy did not impact the individual relationships of ethical concerns and stigma on levels of support.

Conclusions: Should school systems wish to include AI education in their program, they should influence parents to associate positive attitudes with the innovation.

Keywords: artificial intelligence, AI literacy, parental opinions, ethical concerns, stigma, support.

Tables of Contents

1. Introduction

The current artificial intelligence (AI) boom has brought many changes to society. One of the most notable changes can be seen in job markets all over the globe (Administrator, 2025). AI processes are replacing administrative and data entry positions, chatbots are taking over customer service roles, and demand for delivery drivers is decreasing due to the accessibility of drones and automated driving vehicles. Companies find it cheaper to utilize AI services instead of funding the salaries of several full-time employees (Kelly, 2025). Kelly describes that this created higher levels of anxiety and panic amongst current office workers who fear the security of their positions and earnings.

However, with the loss of previously available work positions arises new opportunities. Many share the opinion that AI doesn't replace jobs; it simply redefines what is expected of employees (Mamut, 2025). Learning to understand and utilize AI will ease the upcoming demands to keep up with automated systems. This change can be seen on job vacancy websites all over the internet; not only are Excel skills a requirement, but AI skills are too. The only way to prepare the future generation for this major shift is to introduce them to AI at a young age and slowly build their skills and familiarity. This need furthers the necessity for children to receive proper AI education starting at an early age.

The discussion of whether or not schools should bring AI education into the standardized school system has been an increasingly hot topic, with two clear groups present in the discussion forum. One group of parents takes note of bad encounters with AI and advises their children to stay away from it (Zhang et al., 2022). The other group is in favor of the inclusion of AI in educational criteria, believing the benefits outweigh the risks of use, and encourages their children to engage with AI.

When ChatGPT rose to fame in early 2022, a guideline was created by AI for Education, a group focused on educating the public on artificial intelligence topics, to give parents a solid breakdown of everything that was necessary to prepare their children to take on a new reality with AI present. This guideline sought to inform parents to increase their AI literacy skills, ease their ethical concerns, and try to decrease stigma against these tools (AI for Education, 2025). This organization believes that these three factors influence the levels of support that parents can have towards including AI education into standardized schooling.

Current research dives deeply into the ethical concerns of AI and how parents attempt to protect their children online. Many mention the possible safety features of each program and how they can or cannot safeguard the younger generation (Wisniewski et al., 2017). Other research shows the increasing importance of AI literacy, known as the capability to use and understand artificial intelligence (Kasinidou, 2023). In academia, however, there is a lack of connection between the qualities of parents and the support for AI education for their children.

Current research showcases the three factors: parental AI literacy, parental ethical concerns of AI, and parental stigma of AI. The AI for Education group infers a connection of each to their support of AI education in schooling. Less AI literacy, an increase in ethical concerns, and the presence of negative attitudes all impact the support parents have towards students taking AI courses in standardized education (Koc & Celik, 2015; Vorobeva et al., 2022). The goal of this research is to gain insight in how the different levels of AI literacy support are displayed amongst parents of students currently or formerly receiving education.

This study is a quantitative analysis measuring these three factors and their perceived impact on the level of support provided by parents of children currently or previously in a brick-and-mortar school system. The data collection will be conducted through surveys sent out in an attempt to answer the following overarching research question.

RQ1: What is the effect of AI literacy, ethical apprehensions, and stigma on parental support towards including AI education in standardized schooling?

The paper will begin with a theoretical framework to introduce important topics and variables related to the study. Then the methods of the study will be explained before the analysis of the data. Lastly, there will be a discussion of the study where the results will be applied to real-world uses, such as future research and policy formation recommendations.

2. Theoretical Framework

In order to start a paper on the different impacts on AI education, it is important to make clear what AI is and where it came from. This chapter will begin by explaining artificial intelligence in Section 2.1, current AI education systems in Section 2.2, AI literacy in Section 2.3, ethical concerns of AI in Section 2.4, stigma towards AI in Section 2.5, and finally, the connection of all variables in Section 2.6.

2.1 Artificial intelligence

2.1.1 History of AI

The history of AI dates back over 70 years. The first recorded description of AI was produced at the Dartmouth Conference on AI in 1956, stating that any machine can be capable of simulating learning tasks so long as they are fed information about the completion process in great detail (Cordeschi, 2007). During this conference, the term ‘artificial intelligence’ made its first appearance, beginning its developmental timeline. Haenlein and Kaplan (2019) describe that the four periods in the timeline of AI can be compared to the characteristics of the four seasons. The Dartmouth Conference identified AI in the springtime, a season known for renewal and birth. The cheerful summer of AI spanned between 1956 and 1980, when hope and optimism for the innovation concept were present; governments and academic institutions pumped funding into further development. Then came a moment of winter. Between 1973 and 1980, harsh criticisms and funding cuts were made towards artificial intelligence as the public became skeptical. Luckily, the fruits of AI persevered to the fall harvest. In the 1990’s deep learning came to life, and the practical uses of AI boomed globally.

2.1.2 Modern AI

Now, AI has become one of modern times' most promising innovations that spans farther than formulas and equations. The modern AI can be defined by De Zúñiga et al. (2023) as “the tangible real-world capability of non-human machines or artificial entities to perform, task solve, communicate, interact, and act logically as it occurs with biological humans” (p. 318). In simpler terms, AI is capable of completing real-world tasks in a human-like way. It can be seen in many different forms, such as in video surveillance systems, automobiles, and even in social media (Sharma et al., 2022). To understand the various applications of artificial intelligence, it is necessary to grasp that there are many different domains of implementation.

Each of the domains corresponds to a field of work in which they are applied. One of the domains uses AI systems such as predictive analysis to tell companies what purchasing behavior they can expect from the advertisements that they post online (Mariani et al., 2021). Predictive analysis AI works as the system is fed historical information about online users and customers (Raji et al., 2024). From this historical data, patterns and models are created. Using these models, companies can not only predict the success of future campaigns, but they can also quickly detect fraud and scam customers.

In another domain, AI can focus on sports topics. For example, AI can be used to improve the weight training process of athletes to optimize workouts with personalized weight selections based on performance statistics (Novatchkov & Baca, 2013). With the technology of cable force sensors, movement sensors, and timers, the algorithms can provide real-time feedback to the athletes about their performance and explain the changes that should be made. In the study conducted by Novatchkov and Baca (2013b), a weight-lifting assistant was created to provide quick advice to those working out via their mobile devices. Thus, bringing AI closer and closer to the public's everyday lives.

2.1.3 Machine Learning

Through these two examples, the basic processes of machine learning, a subset of AI, can be seen. Machine learning is a process seen in several steps (Bell, 2022). The process will start with a large collection of data. Then the data will go through preparation and will be cleaned to remove any inconsistencies or irrelevant information. From there, either a supervised or an unsupervised algorithm must be chosen. A supervised algorithm has prelabeled data, and the goals are already determined by humans. An unsupervised algorithm is free; the data is analyzed without any labels, allowing for hidden relationships to be discovered (Jin, 2020). Through the selected algorithm, the model is trained, then evaluated before finally being deployed for use.

The deployment and use of AI is widely spread across many industries, including the examples stated previously. When this paper refers to AI, it will be in the context of AI machine learning systems available to students, such as interactive AI bots and generative AI.

2.2 Current AI Education

This chapter looks into the current inclusion of AI education in the standardized schooling system. The goal of this chapter is to showcase what the existing educational system curriculum includes, the present integration of AI education, and relevant educational theories.

2.2.1 Modern Educational Systems

To best describe what educational systems are comprised of, this section will differentiate German and Dutch school systems from the American school system.

The Netherlands and Germany have similar education systems; therefore, they are put together in this section. Students are split depending on their selected level of study. At around 10 to 12 years old, students consider their future career aspirations and choose a secondary school that matches their needs and wishes (*The Dutch School System*, 2025; Fidler, 2017). Both countries have basic requirements that each student must meet, regardless of the level of schooling they choose. Requirements include passing courses in their native language, English, and mathematics (Ministerie van Algemene Zaken, 2021). The level of schooling chosen changes how theoretical the courses are and the rigor with which they are taught. Ministries of each region go into a deeper description about what is expected of local schools, however, there remains some wiggle room for the schools themselves to alter their teaching.

On the other hand, the American education system is highly impacted and shaped by external pressures, often striving for high-scoring students and their admittance into prestigious higher education institutions (Ross et al., 2014). Unlike in the Netherlands and Germany, there is no split between the different levels of schooling; each student attends their school based on their location and not their IQ. Issues arose when the public noticed that each state held its students to different standards. Around 2010, the Common Core State Standards (CCSS) were released in response to this matter (Conley et al., 2014). The CCSS is a set of learning expectations for students, which allows students across all states to have the opportunity to receive a consistent quality of education, regardless of where in the country they live. Within these expectations are two major subject areas of focus: English language arts and mathematics (Sineath, 2014; Senn et al., 2013). The goal of CCSS, similar to the educational systems in the Netherlands and Germany, is to align each state to provide all students with the tools and instruction necessary to develop high aptitude for careers or future study.

2.2.2 Dynamic Curricula

In each country is a list of requirements covering the basic teachings that each student must learn. These requirements put emphasis on preparing their students for their future careers or future education. Part of preparing students is keeping up to date with what is needed for them to succeed. An example of this was seen mid 2010's, when industrial enthusiasm brought attention to computer science-related careers (Paul, 2016). Quickly, a skill gap was seen in graduating students between what was expected of them and the skills they had to do so (Kaplancali, 2017). As these students were not introduced to coding during their time in grade school, a university degree in a technical sector was difficult for them to achieve, as they needed to go from beginner to mastery in four years. Since then, schools have started offering coding courses to their students, receiving many positive responses (Vico et al., 2019). As the students are introduced to coding languages and uses from an earlier age, they are better equipped with the knowledge and skills necessary for university and eventually their careers.

As time passes, newer innovations take the stage. Computer science has become a widespread field encompassing many different disciplines. One distinct discipline, artificial intelligence, has recently become the star of the show with increasing levels of public interest. However, there is a lack of AI literacy included in the current global standardized education. The next step towards the future is including AI literacy.

2.3 AI Literacy

Artificial intelligence can now be seen in almost all aspects of work. Its rapid evolution will continue, and there will be increasing speeds to once mundane and time-consuming tasks (Amanov & Pradeep, 2023). With the dynamic nature of AI comes the importance of understanding it. There is no escaping machine intelligence; whether it's recognized or not, artificial intelligence is constantly in use. Lourduraj et al. (2024) state that

AI systems can be used casually, such as voice assistants in mobile phones, in the health sector, such as early diagnoses in scans, and life organization, such as calendar scheduling. Its omnipresence brings an urgency to improve the public's AI literacy.

2.3.1 Definition of AI Literacy

There are several different definitions of AI literacy available on the internet. AI literacy, like other literacies, can be broken down into smaller dimensions or domains. Multiple sources agree on three main concepts of AI literacy. They define AI literacy as a person's competence to know and understand the technology and underlying concepts behind AI, their ability to identify and apply AI in different contexts, and their skills to evaluate and communicate with AI collaboratively and safely (Long et al., 2021; Ng et al., 2021; Pinski & Benlian, 2024). To meet the requirements of the first domain, a person must be able to understand basic processes, such as natural language processing and the previously mentioned machine learning. The second domain requires awareness of artificial intelligence; this comes from the ability to identify AI in the real world and the ability to apply it independently (Yadav et al., 2022). The third and final domain involves a person's capability to use AI tools in a correct and safe manner. Examples of this include identifying generative AI hallucinations, “a phenomenon where artificial intelligence models generate content that is plausible but factually incorrect” (Sidhu, 2025, p. 8). As many human labor career positions are being replaced by automated processes, an increase in skill and knowledge in these three AI literacy domains will result in higher chances of success in careers in the remaining work opportunities. It can be understood that AI literacy includes having both theoretical and practical knowledge related to the innovation.

2.3.2 Frameworks for AI Literacy

With public pressure comes motivation to change. Some schools and educational institutions are at the forefront of including AI literacy into their education curriculum.

Several frameworks have been developed to organize and plan out what exactly should be taught to students.

2.3.2.1 Frameworks: K-12

For students still in grade school, frameworks focus on the early development of skills to use AI tools in an effective and safe manner. In 2018, the Association for the Advancement of Artificial Intelligence (AAAI) worked in collaboration with the Computer Science Teachers Association (CSTA) to create a guideline for American teachers to use when providing AI education to their students (Touretzky et al., 2019). Together, they came up with five big ideas for K-12 AI learning, shown in Table 1.

Table 1
Big Ideas for AI Learning in K-12 Education

Big Idea	**Explanation**	**Educational Context**
Perception	AI systems collect input in different ways, using tools such as sensors and voice recognition devices.	Students should be able to interact with these devices. They will build skills up from interaction to creation.
Representation and Reasoning	Agents, AI systems, maintain models of the world and use them for reasoning.	Students should be able to understand that agents are able to create representations using data, such as graphs and maps.
Learning	"Computers can learn from data."	Students should be able to understand machine learning and pattern creation.
Human-AI Interaction	It is challenging for AI developers to make interactions between agents and humans comfortable.	Students should understand that AI is not capable of utilizing human emotions and behaviors; they should recognize it's limits.
Societal Impact	There are positive and negative impacts that AI has on society.	Students should recognize the impacts of AI on their own lives. They should be able to reflect on uses and ethics.

Other organizations have used frameworks with similar constructs to create their own curricula. Generally, the curricula currently used in younger student education focus on awareness of AI, ethical considerations, and interaction with AI (Bozkurt et al., 2021). Chiu et al. (2021) conducted a study evaluating several AI curricula in grades 7-9. They found that with an increase in AI literacy came higher levels of self-confidence in a student's capabilities to use AI agents. The students developed intrinsic motivation to better their skills, and in turn, simultaneously created positive attitudes towards using artificial intelligence (Chiu et al., 2021; Ng et al., 2021). Students need to gain trust in their perceived confidence so that they can engage with AI tools, feeling assured that they are doing so correctly and safely.

2.3.2.2 Frameworks: University Level and Workforce

Students who finish grade school and choose to move on to higher education face different AI literacy learning goals. Instead of simply identifying AI and understanding its uses and limitations, university students are expected to comprehend artificial intelligence all the way from its origins to its future.

The main goal of university students is to set themselves up with the proper education needed for them to enter the career of their choice. What this translates to in modern times is having a basic level of AI literacy. Microsoft, a globally recognized technology company, states in their 4th Annual Trend Index report that most companies will not hire an applicant that does not have AI skills (Okemwa, 2024). With this drastic change in the employment sector, it is necessary to prepare students in their higher education institutions.

Some institutions have already incorporated courses to help lessen the present skill gap. The frameworks for university-level AI literacy development have similar domains to those presented in the K-12 framework. However, higher education students are expected to go further in-depth. Instead of acknowledging ethical concerns for artificial intelligence use, they are expected to anticipate future ethical considerations as agents advance (Zhou &

Schofield, 2024). University-level courses receive students from varying backgrounds and experiences, therefore, the courses for AI literacy take a bottom-up approach, easing students into AI adoption before progressing towards skill mastery. Kong et al. (2021) found that this skill gap elimination leads to a feeling of empowerment in students. There is a higher sense of control and autonomy felt by students who can utilize artificial intelligence.

The same can be said for AI literacy in adults already in the workforce. The perceived skill gap is even larger for late adulthood-aged employees. Often lacking basic terminology and knowledge of technologies, individuals in this demographic face the most challenges in developing AI literacy (Kaur et al., 2021). However, the same source states that while this group faces the steepest learning curve, once their AI literacies develop, they are quickly motivated and can see the benefits of AI technology. Companies are able to cater to their technologically challenged employees by teaching them through non-traditional means. Seya et al. (2020) found that by taking a storytelling and visual learning approach, instead of self-study video courses, adult employees are more likely to understand how to use AI in a shorter time frame. These lessons focus on providing practical knowledge, not mentioning theoretical concepts often found in K-12 and university-level frameworks.

With more and more courses becoming available to the public, trends in AI literacy support came to light. A literature review conducted by Chetty (2023), covering topics on AI literacy and the aging workforce, found that as employees increase their AI literacy, they feel more connected to the digital economy. The same source states that they feel as though they are able to contribute to society in a valued way. This positive outlook is hypothesized to transfer to their support for including AI into education systems. Since a higher artificial intelligence literacy rate increases the amount of perceived positive outcomes in society, it can be naturally inferred that parents would have higher support for their own children to increase their AI literacy rate, resulting in the following hypothesis and model:

H1: The AI literacy level of a parent increases their support towards including AI education in standardized schooling.

Figure 1

Model of AI Literacy and Level of Support Relationship

2.3.3 Assessing AI Literacy

As there were three domains found when defining AI literacy, they will each be addressed in the scaling. Hornberger et al. (2023) created an instrument containing items of multiple dimensions often associated with AI literacy, including AI concepts, AI applications, and AI ethics. The researchers involved in this study noticed a lack of knowledge on AI literacy skills of those who are not specifically associated with an AI literacy course, and decided to create a multiple-choice exam to assign each person in the general public a numerical AI literacy score. This instrument will be used in this study.

2.4 Ethical Concerns of AI

This chapter will look into the common ethical concerns regarding AI. As there are too many to mention in this theoretical framework, the three most covered concerns in academia will be mentioned: discriminatory bias, data privacy, and autonomy. Following this will be a section describing how the possession of ethical concerns towards AI impacts a person's support for AI literacy and inclusion.

2.4.1 Discriminatory Bias

One of the top concerns parents have when addressing the ethics of AI in schools is how susceptible students are to bias presented by the algorithm. Bias in AI arises when the data used to train AI holds prejudices that are recreated into AI's output, and, in some cases, transformed to hold greater or different meaning (Ferrer et al., 2021). This is concerning in the context of young students, as there are negative outcomes that can stem from repeated use of AI. In a school environment, AI sorting systems may label a student as not fit for an accelerated program based on their last name or ethnicity. This leaves the students feeling discouraged and downcast, potentially impacting their work in school. Artificial intelligence systems, especially generative ones, are very difficult to control. In a study conducted by Baines et al. (2024), the capabilities of image-generating AI for storytelling were tested concerning the bias they represent in gender and ethnicity. The findings concluded that there was a noticeable impact made by these images on the children's perceptions of stereotypes (Endendijk et al., 2013). This shows the vulnerability of students, encouraging students to use AI, as they are susceptible to potentially discriminatory outputs.

2.4.2 Data Privacy

Data privacy is a common concern that the general population brings up in the discussion of AI ethics. When a person signs up for a website, app, or any other program, they sign away their rights to their data. Oftentimes, users do so unknowingly and lose track of their data when they stop using the application or when the company goes out of business (Estrada-Galiñanes & Wac, 2019). These companies collect large data files from online users that can contain their user information, behavioral data, demographic data, and even health data (Andreotta et al., 2021). These data sets can identify sensitive information that the user might not want to be spread or used by other parties.

The concerns of the general population increase when addressing a younger audience. Parents have concerns about their children becoming 'datafied' when using AI without supervision and agreeing to unwanted data collection procedures (Lupton & Williamson, 2017). Datafication of a person can be described as transforming their technology interactions and descriptive metrics into dynamic numbers that can be used in analysis to find patterns and create predictions (Mai, 2016). Duhigg (2012) writes in the New York Times about an example of datafication occurring. Duhigg describes how Target, a large-scale American retail corporation, developed a data analysis model, the pregnancy-prediction model, to assign each customer a score of how likely it is that they are pregnant. This brought anger to a father located in Minneapolis. Suddenly, his teenage daughter was receiving personalized maternity advertisements and coupons for baby supplies. He had no idea that his daughter was pregnant and criticized the company for encouraging teenage pregnancy. However, he decided to dig deeper into this situation and found out that his daughter was truly with child and had not yet announced this to the family. She was datafied, her privacy was taken away from her, and her choice to share her pregnancy with her father or not was taken away. She was unaware that Target was collecting this data from her. Simply because she was a female and was purchasing items flagged by the pregnancy-prediction model, she was forced into an uncomfortable situation.

As more data analysis models are created, the likelihood that these corporations know more about children than their parents increases. This is a stark cause of worry for parents in this generation. Thus, data privacy issues can be linked to a decrease in support as parents wish for their children's data to remain their own.

2.4.3 Autonomy

Another large concern of parents is the impact that artificial intelligence can have on a student's autonomy. Autonomy can be referred to as a person's "capability to act on the basis of beliefs, values, motivation, and reasons that are in some important sense [their] own" (Prunkl, 2024, p. 5). In the context of AI, the autonomy of a person can be endangered when they are nudged and targeted by content. Algorithms and generative AI have the ability to manipulate viewers into swaying from their inner morals and beliefs by means of personalized advertisements, pushing addictive content in a scroll, or even by not being transparent about the workings of an application (Laitinen & Sahlgren, 2021). Not only can

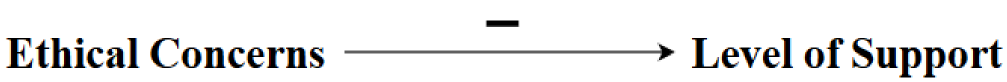
AI systems impact the psychological sides of autonomy, but also a person's functional autonomy. Increasing over-reliance on these systems decreases the need for students to establish and develop academic skills such as text analysis and summarization (Macnamara et al., 2024). Thus, the collective impacts of AI on autonomy can be seen by parents in a negative light.

2.4.4 Impact of Concern on Support

When looking at a student's susceptibility to discriminatory bias, unknowing personal data collection, and a decrease in autonomy, there is a lot for a parent to consider when creating their opinions towards their advocacy of AI education. Through a cross-national survey of 396 participants, Perella-Holfeld et al. (2024) found that the more a parent is concerned with the ethical aspects of AI, the less comfortable they feel allowing their children to interact with AI on their own. Parents would prefer that their children be under supervision while using these systems. Applying this idea towards the support a parent has in including AI literacy in standardized education, where teacher-to-student ratios average at one to 25, it can be expected that parents with higher concern levels will have less support towards these courses (Koc & Celik, 2015). This relationship can be represented in the following hypothesis and model:

H2: The ethical apprehensions of a parent decreases their support towards including AI education in standardized schooling.

Figure 2
Model of Ethical Concerns and Level of Support Relationship



2.4.5 Scaling of Ethical Concerns

AI stretches over many modern working sectors, sparking discussion worldwide. Saatci (2025) took an interest in this topic and conducted a survey study to measure the levels of ethical concerns adults have towards this widespread inclusion of AI. After a deep literature review, five dimensions of ethical concerns were identified. The first was transparency, which is often linked with the autonomy of the user. Then came data privacy and fairness, which can also be referred to as bias. Lastly was accountability and human oversight. From these five dimensions, the AI and Ethics Perception Scale (AEPS) was created, a 35-item, reliable and valid scale tested on a pilot and full study. As the AEPS is a tool for empirical measurement of AI ethical concerns, its items will be taken and adapted to suit the needs of this study.

2.5 Attitudes and Stigma

The positive and negative attitudes an individual has towards an object or person is a starting point to be able to understand their deeper beliefs and stereotypes. In the world of technology, attitudes, either positive or negative, contribute to the creation of stigma.

Stigma is seen as a social phenomenon that can lead to marginalization and discrimination. In a conceptual analysis aimed at defining the term 'stigma, Andersen et al. (2022) describe several requirements to prove the presence of stigma. The first is that there are labeled differences present in a society. When relating to AI, examples of these groups include those who utilize AI, those advocating for AI, those against AI, etc. The second requirement is that there is negative stereotyping present. This can occur if the group that utilizes AI labels those in the group who do not use AI as technologically incompetent, or when those against AI call those who do as 'less capable' or 'lazy' (Vorobeva et al., 2022). Then comes the third requirement, which will show a visible polarization between all groups, making it clear to the general eye to which group a person belongs based on their actions and opinions. Once group formation and the "us vs. them" mentality are developed, then comes the final requirement. Each group will then create a status ranking of each of the others, usually determining that those in groups other than their own are of lesser quality. Using the AI example, after being stereotyped as lazy, the AI group has lost credibility and respect in the eyes of the group against AI, completing the process of stigma in regards to AI.

Stigma is a result of multiple stages of attitude assessments and labeling in a population or community. It is also an important factor in the acceptance of any technology or innovation into society. Negative attitudes result in the presence of stigma, which in turn result in less public support. The Technology Acceptance Model (TAM) by Davis (1989) shows how multiple factors go into an individual's decision to use a new technology. Starting from perceived usefulness and ease of use, this model takes into account the positive or negative opinions a person has and showcases how that may lead to their decision of using the technology or not. This emphasizes the importance of looking into parental attitudes and the presence of stigma when researching their support towards accepting and including AI literacy courses into standardized education. A parent with negative stigma is less likely to want their child to engage with AI compared to a parent with positive stigma. The latter presumably would offer their full support and encouragement, represented in the following hypothesis and model:

H3: Parents with a negative stigma towards AI have lower support for including AI education in standardized schooling.

Figure 3
Model of Stigma and Level of Support Relationship

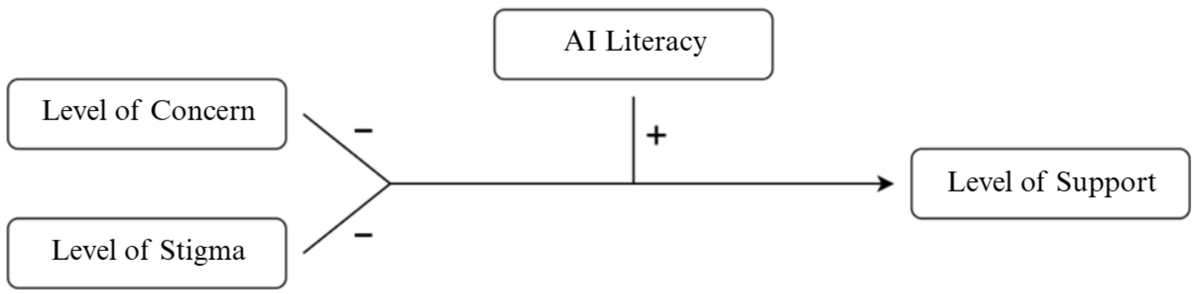
2.6 Connection of Variables

As found out in the literature, AI literacy is directly connected to ethical concern levels and stigma. A highly AI literate parent perceives AI education in a positive light and is less concerned about ethical issues connected to it. The level of ethical concern a parent has towards AI education is negatively correlated to their support levels; this negative correlation is also seen with the increased presence of stigma. What remains unmentioned in academia is the interaction of all three factors on the overall impact on parental level of support towards AI education in standardized education. Therefore, the following hypothesis is constructed:

H4: AI literacy will significantly interact with the relationship between the level of concern and the level of stigma on the level of support.

In this concluding section of the theoretical framework chapter, the previously defined variables will be put in the direct context of the study. In each section, a hypothesis and model are presented based on previous literature, showcasing the predicted interaction between each independent variable to the level of support a parent can have towards including AI education in standardized schooling. The following model, Figure 4, shows the expected joint impact relation mentioned in this section.

Figure 4
Model of Moderation Relationship between all Variables



3. Methods

The following section will explain the research design of this study, delving into the quantitative data collection method, description of the sample, and content validity of the survey.

3.1 Design

The aim of this study was to visualize and understand the relationship between AI literacy, ethical concerns towards AI, and attitudes on AI on parental support towards including AI education into standardized schooling. The design of the study was a quantitative survey analysis. This data collection method was selected as it provides a large amount of data that is collected at a single moment in time. Davis (2011) describes survey data as a valuable source for getting “at a glance” impressions of the participants' attitudes and beliefs. The unbiased collection method effectively measures multiple variables across a large sample (Hasan, 2024). This quick and simplified data collection is the best method for this study as it allows for a clean relationship establishment between variables.

3.2 Procedure

The first step in this study was to create a pre-test interview to determine the relevance of the concepts and topics found in related research. These short 15-minute interviews were conducted to test whether the participants were able to form an opinion on topics related to each of the variables. If they could back up their ideas, then it was understood that their opinions were founded on background knowledge and not made blindly. It was ideal to avoid including topics in the survey that the participants in the sample interview knew nothing about.

The interviews were held with three participants, as the final survey was offered in three languages (Dutch, English, and German), there was one participant interviewed from each of the presented languages. This 15-minute interview was semi-structured, allowing the participants to either elaborate extensively on the topic or move on. Questions asked in the interview align directly with the draft of the survey, see Appendix 1. At the end, there was time for the participant to voice other matters they wished to be represented in the survey. From the responses of the interviews, the survey was not adjusted as the parents were able to recognize and comment on each topic and concept presented.

3.2.1 Instruments: Survey Construction

The survey itself consisted of 26 items spread across five sections, as seen in Appendix 2.

Before starting the survey, participants read through the informed consent form approved by the Ethics Committee of the University of Twente and then chose to either end the survey or move forward. If the decision was made to move forward, the participants were led to the first section, which consisted of non-identifying demographic questions. The questions were later used in the analysis to test for demographic differences between the variables.

The second section of the survey measured the participants' AI literacy. This was done using the three dimensions established in the theoretical framework. Using the scale created by Hornberger et al. (2023) in their study measuring the AI literacy levels of German university students, two items were selected to represent each of the dimensions. A total of six multiple-choice items were provided for this section. Shown below in Table 2 is an example of one item from each dimension.

Table 2

Examples of Survey Items for AI Literacy

Dimension	Question	Answer Choices
AI Applications	In which of these areas is AI typically applied?	- **Detecting credit card fraud** - Cryptocurrency mining -Web tracking - Encryption for instant messaging services

AI Concepts	How do AI systems make decisions?	**- Based on mathematical-logical principles** - based on links defined by programmers - based on quantum entanglement - based on artificial intuition
AI Ethics and Safety	What are central risks in using AI for predictive policing?	- Vulnerability to hacking **- Discrimination against suspects based on origin and status** - Lack of legal certainty in the event of AI breakdown - Undermining the authority of police officers

Note: Correct answers to the questions are presented in bold.

The third section measured the level of concern a parent had when addressing the ethics of AI. Six items were answered using a five-point Likert scale. The items were taken from the AI and Ethics Perception Scale (AEPS) created through a systematic process by Saatci (2025). The items were slightly altered to remove content connecting AI to the workplace and changed to address a general and overarching concept of AI.

The fourth section used an existing AI attitude measurement scale. For decades, researchers have been looking for the best ways to scientifically measure attitudes. Grassini (2023) sought to create an instrument to measure attitudes towards AI. This was done through an in-depth literature review analyzing existing and relevant research on AI attitudes. Theories that were commonly mentioned and TAM were combined to identify several dimensions of AI attitudes. At the end of the study, a four-item scale was validated and published for open access. This study utilized all four items, plus an extra item that was taken out in the testing stages of Grassini's scale, but was deemed relevant for this research.

The fifth and final section measured the support that parents had and expressed towards AI education being included in standardized schooling. As this topic is either not published or researched yet in academia, there were no existing scales to be used or altered to fit this study's purpose. Therefore, four Likert scale items were self-designed to measure this variable. With these five sections, the survey was complete.

3.3 Validity and Reliability

To ensure content validity of the survey, survey items were based on academically peer-reviewed literature. In the AI literacy section of the survey, three dimensions of AI were chosen from the definition provided in the theoretical framework. Two items from each dimension were chosen from an existing scale. The same can be said about the third and fourth sections of the survey, measuring AI concern and attitudes, respectively. The final section of the survey was the only portion self-designed.

When considering the reliability of the Likert scales, the consistency of the survey's measurement over the data collection periods was evaluated. A Cronbach's alpha is a statistic available to determine the relatedness of each item in a group. For example, each item in the ethical concern Likert scale should be ranked similarly if the participant has a clear opinion formed towards that topic. The Cronbach's alpha for each of the Likert scale items can be seen in Table 3. Each variable is described as a factor; factor one includes inverse items measuring ethical concerns, factor two includes items measuring stigma, and factor three includes items measuring level of support.

Table 3
Factor Analysis

	Factor		
Statements	1	2	3
AI systems are regularly audited to ensure that human intervention can override AI decisions if necessary.	0.78		
AI systems are tested for fairness before deployment.	0.78		
AI systems ensure that user data is anonymized where applicable.	0.80		
I trust the decision-making process of AI systems.	0.80		
AI systems comply with national and international data protection regulations.	0.82		

Discrimination through AI is prevented through regular system audits.	0.80		
I believe that AI will improve my life.		0.86	
I believe that AI will improve my work.		0.84	
I think I will use AI technology in the future.		0.86	
I think AI technology is a threat to humans.		0.89	
I think AI technology is positive for humanity.		0.85	
I believe AI literacy should be included in standardized education.			0.78
An increased AI literacy will provide an advantage when applying for jobs.			0.87
AI literacy is as important as other grade school subjects.			0.82
It is important for children to understand how to use and navigate AI tools.			0.78
Cronbach Alpha:	0.83	0.88	0.85
Explained Variance:	44.99%	61.97%	61.50%
Eigenvalue:	2.69	3.09	2.46

A reported alpha between 0.70 and 0.79 is considered to be acceptable, an alpha between 0.80 and 0.89 is considered good, and an alpha of 0.90 or higher is considered to be great (Tavakol & Dennick, 2011). The lowest Cronbach's alpha in the survey is 0.78, which shows that the survey items were reliable. The most reliable factor was stigma; items in this section have the strongest group to item relatedness.

3.4 Sample

The participants of the study were parents or guardians of students who are currently or were previously in a brick-and-mortar school. Brick-and-mortar schools include all grades and study levels, ranging from kindergarten to graduate school. Parents whose children have attended such institutions are familiar with education criteria, standardized goals, and lesson requirements, therefore meaning they are likely to have more to express in regards to AI being included. Parents who have homeschooled their children or parents of virtually schooled children will be disqualified from participation.

To reach out to the sample, several methods were used over the course of three weeks. Personal connections were the main contact method. The researcher reached out to parents in their circles and asked for collaboration in spreading the survey around. The survey was also posted on social media sites and in groups where parents are highly active. Examples of this include different local parent associations or university parent groups on Facebook. At the end of the collection, there was a total of 91 participants. After taking out surveys that were not completed by the target group, completed too quickly, or were incomplete, there was a total of 69 full surveys eligible to be used for analysis.

3.3.1 Description of Sample based on Survey

The following table, Table 4, shows the distribution of demographics from the surveys. The majority of participants were in their forties or fifties. Gender was split evenly. There was a relatively even percentage from each country of residence, with a few submissions from other non-specified countries. In regard to the number of children that the participants had, 29.1% had one child and 53.6% had two children. Most of the parents had older children, having upper secondary school or university or college as the highest level of education.

Table 4

Demographic Distribution of Survey Participants

Age	**Frequency**	**Percent (%)**
30-39	2	2.9
40-49	24	34.8
50-59	35	50.7
60-69	8	11.6
Total	**69**	**100**
Gender	**Frequency**	**Percent (%)**
Male	33	47.8
Female	35	50.8
Prefer not to say	1	1.4
Total	**69**	**100**
Country	**Frequency**	**Percent (%)**

Germany	24	34.8
The Netherlands	18	26.1
The United States	20	29.0
Other	7	10.1
Total	**69**	**100**
Number of Children	**Frequency**	**Percent (%)**
One	20	29.1
Two	37	53.6
Three	7	10.1
Four (+)	5	7.2
Total	**69**	**100**
Highest School Level of Children	**Frequency**	**Percent (%)**
Primary School	4	5.8
Lower Secondary School	6	8.7
Upper Secondary School	16	23.2
University or College	43	62.3
Total	**69**	**100**

3.5 Data Analysis

After data collection, the results from the survey were put into the statistical programming software R. Here, the dataset was transformed into the proper format and cleaned to only contain complete surveys from participants fitting the qualifications of the sample. Incomplete surveys were removed at this time as well.

Demographic analysis on the participants were ran to best describe the sample. The results of this analysis were shown in section 3.3.1. The descriptive statistics from each item include the mean, median, standard deviation and frequency. Once collected, the results were formatted into an APA style table.

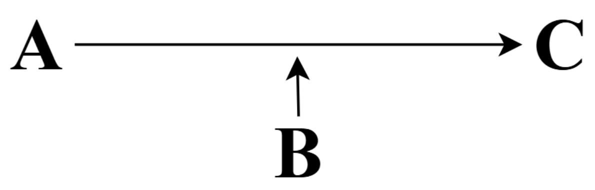
Following the demographic analysis, the same descriptive statistics were taken from each dependent and independent variable: level of support for AI education, AI literacy, ethical concerns, and stigma. Before, these statistics could be calculated, each item needed to be transformed into a workable format for analysis. The items for AI literacy were transformed into a single score variable consisting of the number of correct answers they had for the multiple-choice questions. The items for Likert scale variables, such as ethical concerns, stigma, and level of support, were transformed numerically and then averaged per variable. All ethical concern items and one stigma item needed to be reversed before calculation, as they are inverse items. Once the dataset was in the correct format, the frequencies, means, and standard deviations were checked across each variable.

To answer the hypotheses H1-H3, correlation analyses were conducted three times. One to check the correlation between AI literacy score and level of support, one to check the correlation between ethical concerns and level of support, and one to check stigma and level of support. From this analysis, a Pearson correlation coefficient explained the relationship between the two variables. Telling the strength of the relationship and whether it is positive or negative. After the correlations were established, a linear regression was run to create a prediction model for the level of support based on the singular variable.

To answer hypothesis H4, a moderation analysis was conducted. Moderation analyses check the impact that an independent variable, B, has on the correlation between another independent variable, A, and a dependent variable, C. Figure 5 visualizes this model below. In the context of this study, the variable A is the combined items of stigma and ethical concerns, the variable B is the AI literacy score, and the dependent variable C is the level of support.

Figure 5

Model of Moderation Relationship between all Variables



The moderation relationship model in R, showed the interaction coefficient of the impact that variable B has on variable A and C's relationship. This analysis was conducted three times. Once for AI literacy's impact on the relationship between ethical concerns and level of support, once more for AI literacy's impact on the relationship between stigma and level of support, and one final time for AI literacy's impact on the relationship between the combined variable of stigma and ethical concerns on level of support.

The main research question was addressed by a multivariate regression analysis. From this coefficients and p-values state the effect each independent variable has on level of support. The analysis resulted in a filled-out equation of the following format.

$$Support = \beta_0 + \beta_1 \times AI\ Literacy + \beta_2 \times Ethical\ Concerns + \beta_3 \times Stigma + \in$$

This equation was calculated for the overall sample, so that by having a parent's AI literacy score, ethical concern measurement and stigma measurement, and estimated level of support can be predicted.

4. Results

This chapter will go over the findings of the analysis described in the methods section. This chapter will first cover the descriptive statistics of each variable. Then, the correlation analysis between each independent variable and the dependent variable will be explained, followed by the moderation analyses. Lastly, the results of a multilinear regression will be showcased to fill in the equation presented in section 3.5.

For clarification, this chapter will refer to the different variables in shorter terms. The number of correct responses to AI literacy multiple-choice questions will be referred to as 'AI literacy'. The average amount of concern presented in Likert scale items will be referred to as 'ethical concerns'. The average stigma presented will be referred to as 'stigma'. Lastly, the average Likert scale response per participant for support towards including AI education in standardized schooling will be referred to as 'level of support'.

4.1 Descriptive Statistics

The mean, median and mode were taken for each variable. The following table, Table 5, showcases each variable and their statistics for sample size n=69. AI literacy was measured in number of correct answers to artificial intelligence-related questions, with six total questions. Ethical concerns, stigma and support were measured on a 1-5 Likert scale, with 1 representing 'strongly disagree', 3 representing 'neutral', and 5 representing 'strongly agree'.

Table 5
Descriptive Statistics of Variables

Variable	M	Mdn	SD
AI Literacy	3.03	3	1.67
Ethical Concerns	2.97	3	0.75
Stigma	2.62	2.6	0.88
Support	3.62	3.75	0.97

Note: N = 69

4.2 Correlation Analysis and Linear Regressions

A correlation analysis was performed on each individual independent variable on the level of support. The Pearson's coefficient and p-value were evaluated for each relationship. Afterwards, a linear regression was ran to create an equation to predict the level of support based on each variable. The statistics of each are represented in Table 6.

Table 6
Sample Table Showing Pearson's r and Regression Coefficients

Variable	Pearson's *r*	Regression Coefficient (*b*)	R^2
AI literacy	0.65**	0.38**	0.43
Ethical Concern	-0.53**	-0.14*	0.10
Stigma	-0.81**	-0.36**	0.46

Note: N = 69, $p < .01$*, $p < .001$**

The correlation between AI literacy score and level of support had significant evidence of being positive and real (r = .65, $p < .01$). The linear regression ran on this relationship supported this, $F(1, 67) = 49.64$, $p < .01$, and R^2 of .43. The predictor variable from the regression (b) was 0.38, explaining 43% of the variance in level of support based on AI literacy score. This result supports Hypothesis 1 presented in Section 2.3.

The correlation between ethical concern and level of support was significant and negative ($r = -0.53$, $p < 0.01$). This correlation is linked with Hypothesis 2, presented in Section 2.4. The linear regression showed that the relationship is negative but cannot be predicted well, $F(1, 67) = 7.49$, $p < 0.01$, and R^2 of .10. The variance of 10% showed that the model did not strongly suit the data, and the predictor value (b) of -0.14 can only explain a small portion of the variance in level of support based on ethical concern.

The correlation between stigma and level of support had significant evidence of a strong negative interaction ($r = -0.81$, $p < .01$). Linear regression analysis, ran to prove Hypothesis 3 in Section 2.5, further showed that the predictor value (b) of -0.36 explained 46% of the variance in level of support explained by stigma, $F(1, 67) = 56.63$, $p < .01$, and R^2 of .46.

4.3 Moderation Analysis for Joint Relationship

The moderation analysis was conducted three times to test Hypothesis 4, presented in Section 2.6. The first moderation analysis tested how AI literacy affects the relationship between ethical concerns and level of support, $F(3, 65) = 25.8$, $p < .001$, and R^2 of .52. The results of this analysis are presented in Table 7. The interaction term was shown as the estimate for the coefficient "Ethical Concerns:Score". This estimate showed how much the effect of ethical concerns on the level of support was explained by the inclusion of the AI literacy score. The effect of ethical concerns on level of support was not impacted by AI literacy ($b = 0.03$, $p = 0.69$). There was no significant evidence that this moderation exists in the data.

Table 7

Moderation Analysis of AI Literacy on Ethical Concerns and Level of Support

Coefficients	Estimate	*SE*	*t*	*p*
(Intercept)	4.04	0.74	5.84	$1.85e^{-07}$
Ethical concerns	-0.55	0.23	-2.39	.019
Score	0.23	0.21	1.08	.283
Ethical Concerns:Score	0.03	0.07	0.41	.696

The second moderation analysis was conducted to test for the interaction term of AI literacy on stigma's relationship with the level of support, $F(3, 65) = 48.97$, $p < .001$, and R^2 of .68. The coefficient of "Sigma:Score" was the effect of level of stigma has on the level of support, explained by the inclusion of the AI literacy score. The model, shown in Table 8, suited the sample data well and showed that the moderation interaction from the analysis was insignificant ($b = 0.91$, $p = .069$).

Table 8

Moderation Analysis of AI Literacy on Stigma and Level of Support

Coefficients	Estimate	*SE*	*t*	*p*
(Intercept)	6.09	0.61	10.03	$7.93e^{-15}$
Stigma	-1.03	0.18	-5.62	$4.28e^{-07}$
Score	-0.13	0.14	-0.93	.357
Stigma:Score	0.09	0.49	1.84	.069

The final moderation analysis was conducted to test for the interaction term of AI literacy on stigma's relationship with the level of support, $F(3, 65) = 41.7$, $p < .001$, and R^2 of .64. The interaction from the analysis shown in Table 9 was insignificant ($b = 0.09$, $p = .07$). The coefficient "Combined" was the impact of both ethical concerns and stigma on the level of support for AI education. The coefficient "Combined:Score" was the level of support towards AI education from the combined ethical concerns and stigma, explained by the parents' AI literacy score. There was no statistical evidence that AI literacy impacts the relationship between ethical concerns and stigma on the level of support.

Table 9

Moderation Analysis of AI Literacy on Combined Variable and Level of Support

Coefficients	**Estimate**	***SE***	***t***	***p***
(Intercept)	3.09	0.17	17.84	$< 2e^{-16}$
Combined	-0.42	0.09	-4.73	$1.25e^{-05}$
Score	0.19	0.05	3.83	<.001
Combined:Score	0.04	0.02	1.48	0.14

4.4 Equation Formulation

A multilinear regression was ran to create an equation to predict the level of support a parent has towards supporting AI education based off of their AI literacy score, ethical concerns, and stigma. The regression model showed strong predictive abilities, $F(3, 65) = 47.25$, $p < .001$, and R^2 of .67. The results of the regression can be seen in the following table and equation.

Table 10

Moderation Analysis of AI Literacy on Combined Variable and Level of Support

Coefficients	**Estimate**	***SE***	***t-value***	***p-value***
(Intercept)	5.44	0.43	12.55	$< 2e^{-16}$
AI Literacy	0.12	0.06	2.18	.033
Ethical Concerns	-0.15	0.11	-1.32	.192
Stigma	-0.68	0.12	-5.44	$8.6e^{-07}$

$$Support = 5.44 + 0.12 \times AI\ Literacy - 0.15 \times Ethical\ Concerns - 0.68 \times Stigma + \in$$

This equation showed that the starting point of support is past the boundaries, presenting high levels. With the addition of ethical concerns and stigma, level of support decreased at a higher rate than the increase AI literacy brings.

5. Discussion

This study took a quantitative approach to discover what influenced parents to support AI education. The final chapter will cover the implications of the analysis of the survey data, starting with what the results mean in regards to the research question and hypotheses. In the next subsection, the comparisons between the results of the study and what can be found in existing literature will be made. Limitations will be discussed in the second-to-last section, and the conclusion will finalize the paper.

5.1 Hypotheses and RQ

The first hypothesis assumes a positive relationship between a parent's AI literacy and the level of support they express towards including AI education into standardized schooling. A strong positive relationship was discovered from the correlation analysis. The regression analysis delved deeper and showed that for every increase of AI literacy, the parents' support levels would increase by 0.38. This shows significant evidence supporting the hypothesis statement.

The second and third hypotheses supplied similar assumptions to those of the first. However, the presence of ethical concerns and stigma was speculated to have a negative impact on the level of support that parents have towards AI education. This was supported by the correlation analysis. Both variables had strong negative relationships with the level of support. Stigma, however, had a significantly stronger connection to the measured level of support than ethical concerns. The regression coefficients supported this discovery, as there was a larger negative coefficient for stigma than for ethical concerns.

The fourth hypothesis assumed that the presence of AI literacy would change the relationship between increased ethical concerns and stigma on the level of support. The first two moderation analyses showed that AI literacy did not significantly impact how ethical concerns interacted with the levels of support; the same can be said about how AI literacy impacted the relationship between stigma and levels of support. The model presented in section 2.5 suggested that AI literacy would have a statistically measurable moderation on the combined variable of ethical concerns and stigma. This hypothesis was not supported; the model showed that there was no evidence of AI literacy impacting the combined variable.

The main goal of the study was to discover the overall impact that three individual variables had on the level of support for AI education. This can be seen in the research question stated at the end of the introduction. To best understand the impacts, a multilinear regression model showed how each variable directly influenced levels of support. From the model, it was discovered that each variable had a measurable interaction, but stigma showed the strongest influence. With each numerical increase in stigma, a parent's predicted level of support would decrease significantly. This reported interaction was stronger than the others. AI literacy, the only positive interaction variable, showed to have the least impact in comparison to the rest, as its coefficient was closest to zero. This leaves the presence of ethical concerns to take the middle ranking in terms of influence on the level of support.

5.2 Comparison to Literature

From the findings of the study, there are many similarities to existing research. The average AI literacy score found from the survey analysis is in line with the discoveries of Kaur et al. (2021), who looked into the AI literacy scores of older adults. Just as in their survey response, there was a low number of correctly answered multiple-choice questions among the whole sample. However, this paper differs slightly as it also looks at participants who are in their 40s and a few who are in their 30s. This means the findings of Kaur et al.

(2021) can be expanded to describe the AI literacy score of a wider age range than just that of older adults. Adults, starting in their 30s, have a low AI literacy score.

Not only did the parents' AI literacy rates perform as expected, but their ethical concern interactions on the level of support did as well. In a larger-scale survey study conducted on parental opinions, Perella-Holfeld et al. (2024) discovered that with an increase of ethical concerns present comes an increase of unease in letting their children interact with AI systems. The research presented in this paper backs up these claims as there was significant negative relationship between presence of ethical concerns in parents and their levels of support for AI education. Just as the other research suggests, the more concerned a parent is about the ethics of AI, the more likely it is that they do not wish for their children to interact with it in school.

The strongest connection to existing literature is seen when addressing the Technology Acceptance Model by Davis (1989). While this paper does not follow the entire timeline of how AI education is accepted into society, it takes a look at one specific group at one specific point in time. The TAM highlights the importance of attitudes in the process of acceptance. This importance was also seen in the survey results. The variable with the most influence on parental levels of support for AI education was attitudes, also referred to as stigma. Just as the model suggests, negative attitudes results in lower acceptance and support.

While most of the results support existing knowledge and theory, one section of the findings went against what was found in literature. The survey analysis found no significant moderation from AI literacy's impact on the relationships between ethical concerns and level of support and stigma and level of support. As ethical concerns are considered a part of AI literacy, and an increase of AI literacy includes confidence in capabilities and an increase of positive attitudes, then the inclusion of AI literacy should have influenced the effects of the other previously mentioned relationships (Chiu et al., 2021; Wong et al., 2020). This was not the case in the analysis as no statistically significant results supported this idea. What could be determined from this is that the items used to test ethical concerns and stigma are independent and are not from the domains relation to ethical concerns and stigma typically associated with AI literacy.

5.3 Limitations

The findings of this study are not generalizable to the population, as the sample limits its representativeness. The sample consisted of 91 participants; however, once the unusable surveys were taken out, only 69 remained. The surveys were removed due to them being incomplete, or the participants were not of the targeted sample. This removed a large portion of responses and reduced the statistical power of the results. Another limitation of the sample was the distribution of demographics. The survey itself was presented in English, Dutch, and German, allowing for there to be an equal split within the sample. Since the number of usable surveys were below 90, there were less than 30 surveys taken in each language. This meant that comparisons between countries of residency, an asked demographic question, could not be made, N>30.

Majority of respondents resided in western countries, limiting its broader implications. The reasonings as to why the survey respondents remained in North America and Europe was because of snowball sampling. The researcher sent the survey out to parents in their circles. From there, the survey link was spread further to other circles. As a consequence of this, majority of parents that filled in the survey had children who were already university level or graduated.

The survey design of the study created the possibility for participants to misreport their true opinions and attitudes. As AI is a highly spoken about topic in media, many sources are pushing for public acceptance of the technologies. Parents might have felt the need to answer the survey in a socially desirable way, not representing this own thoughts. Even if the parent does not feel the pressure to report their answers uniformly to the outside world, it is difficult to translate what one is truly feeling into a five-option Likert scale response.

Future research should consider focusing on a smaller specified region instead of an overall outreach. By picking a single country, or even a small region, the researcher has higher chances of statistically significant and representative results, though at the expense of less generalizable findings. Since the study would be smaller, a more in-depth approach could be taken. In order to avoid misreporting from surveys, the researcher could opt for small interviews with parents, allowing for the exploration of unpredicted themes.

5.4 Implications

This study provided a better understanding of what contributes to parental opinions towards including AI into standardized education. Schools wishing to incorporate AI education into their curriculum can use these findings to increase levels of support from parents. As found in the theoretical framework, AI literacy is not included in most education system criteria. Meaning, it is up to each school individually if they would like to offer such courses or not. As there is no regulation to back up these institutions, it is in the school's best interest to persuade the parents to support their initiatives through a hands-on process. Providing an AI educational night for parents to come and understand all things artificial intelligence will not only boost their own AI literacy but also decrease ethical concerns and increase positive attitudes, all of which were shown to increase parental levels of support. Increased parental support may, in the future, lead to changes in policy and educational criteria.

Theoretical implications can be seen in the research world. Future researchers can take the findings and pursue this study further in depth. By using the knowledge of how attitudes impact parental levels of support for education the most, they can choose to look into whether or not it would be more appropriate to rid negative attitudes or generate more positive ones.

5.5 Concluding Statement

This study looks into the influences of parental AI literacy, perception of ethical concerns, and stigma on the levels of support towards including AI education into standardized schooling. Significant evidence showed a positive correlation between AI literacy on levels of support and negative correlations between ethical support on levels of support and stigma on levels of support. Moderation analysis showed that each relationship acts on its own and that parental AI literacy does not change the correlation between ethical concerns and stigma on levels of support. These findings bring insight into how parental opinions can be changed to allow for a new educational curriculum, one in line with AI and modern technological changes.

6. References

Agrawal, A., Gans, J. S., Goldfarb, A., & MitMit Slslooan Manaan Management Review (2017). What to expect from artificial intelligence. In MitMit Slslooan Manaan Management Review. https://static1.squarespace.com/static/578cf5ace58c62ac649ec9ce/t/589a5bfe20099e9d2837a707/1486511104226/What+to+Expect+From+Artificial+Intelligence.pdf

AI for Education. (2025). *What parents & caregivers should know*. https://static1.squarespace.com/static/64398599b0c21f1705fb8fb3/t/682f3b81d1f455327f5ab6e1/1747925889680/AI+in+Education+What+Parents+%26+Caregivers+Should+Know+%284%29.pdf

Amanov, F., & Pradeep, A. (2023). The significance of artificial intelligence in the Second Scientific Revolution - a review. *2022 14th International Conference on Electronics, Computers and Artificial Intelligence (ECAI)*, 01–05. https://doi.org/10.1109/ecai58194.2023.10194056

Andersen, M. M., Varga, S., & Folker, A. P. (2022). On the definition of stigma. *Journal of Evaluation in Clinical Practice*, *28*(5), 847–853. https://doi.org/10.1111/jep.13684

Andreotta, A. J., Kirkham, N., & Rizzi, M. (2021). AI, big data, and the future of consent. *AI & Society*, *37*(4), 1715–1728. https://doi.org/10.1007/s00146-021-01262-5

Baines, A., Gruia, L., Collyer-Hoar, G., & Rubegni, E. (2024). Playgrounds and Prejudices: Exploring Biases in Generative AI For Children. *IDC '24: Proceedings of the 23rd Annual ACM Interaction Design and Children Conference*, *35*, 839–843. https://doi.org/10.1145/3628516.3659404

Ban, O., Maiorescu, I., Bucur, M., Sabou, G. C., & Tzedec, B. C. (2024). AI between Threat and Benefactor for the Competences of the Human Working Force. *Amfiteatru Economic*, *26*(67), 762. https://doi.org/10.24818/ea/2024/67/762

Bell, J. (2022). What is machine learning? In *Machine Learning and the City: Applications in Architecture and Urban Design*. https://doi.org/10.1002/9781119815075

Bhatti, N., Stelter, T. L., McCrickard, S., & Kelliher, A. (2021). Conversational user interfaces as assistive interlocutors for young children's bilingual language acquisition. *ACM International Conference on Interactive Media Experiences*, 208–211. https://doi.org/10.1145/3452918.3465498

Bozkurt, A., Karadeniz, A., Baneres, D., Guerrero-Roldán, A. E., & Rodríguez, M. E. (2021). Artificial Intelligence and Reflections from Educational Landscape: A Review of AI Studies in Half a Century. *Sustainability*, *13*(2), 800. https://doi.org/10.3390/su13020800

Chetty, K. (2023). AI literacy for an Ageing workforce: Leveraging the experience of older workers. *OBM Geriatrics*, *07*(03), 1–17. https://doi.org/10.21926/obm.geriatr.2303243

Chiu, T. K. F., Meng, H., Chai, C., King, I., Wong, S., & Yam, Y. (2021). Creation and evaluation of a pretertiary Artificial Intelligence (AI) curriculum. *IEEE Transactions on Education*, *65*(1), 30–39. https://doi.org/10.1109/te.2021.3085878

Conley, D. T. (2014). The common core state standards: Insight into their development. Washington, DC: Council of Chief State School Officers.

Cordeschi, R. (2007). AI Turns Fifty: Revisiting It's Origins. *Applied Artificial Intelligence*, *21*(4–5), 259–279. https://doi.org/10.1080/08839510701252304

D. Sineath, K. D. S. (2014). The Effect of Classroom Discourse on High School Student's Argumentative Writing Skills [PhD Dissertation, Northeastern University]. https://repository.library.northeastern.edu/files/neu:336532/fulltext.pdf

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, *13*(3), 319. https://doi.org/10.2307/249008

Davis, J. J. (2011). Advertising research: theory and practice. *Choice Reviews Online*, *49*(04), 49–2161. https://doi.org/10.5860/choice.49-2161

De Zúñiga, H. G., Goyanes, M., & Durotoye, T. (2023). A Scholarly Definition of Artificial Intelligence (AI): Advancing AI as a conceptual framework in communication research. *Political Communication*, *41*(2), 317–334. https://doi.org/10.1080/10584609.2023.2290497

Duhigg, C. D. (2012, February 16). How Companies Learn Your Secrets. *The New York Times*. https://www.nytimes.com/2012/02/19/magazine/shopping-habits.html

Endendijk, J. J., Groeneveld, M. G., Van Berkel, S. R., Hallers-Haalboom, E. T., Mesman, J., & Bakermans-Kranenburg, M. J. (2013). Gender stereotypes in the family context: mothers, fathers, and siblings. *Sex Roles*, *68*(9–10), 577–590. https://doi.org/10.1007/s11199-013-0265-4

Estrada-Galiñanes, V., & Wac, K. (2019). Collecting, exploring and sharing personal data: Why, how and where. *Data Science*, *3*(2), 79–106. https://doi.org/10.3233/ds-190025

Ferrer, X., Van Nuenen, T., Such, J. M., Cote, M., & Criado, N. (2021). Bias and Discrimination in AI: A Cross-Disciplinary Perspective. *IEEE Technology and Society Magazine*, *40*(2), 72–80. https://doi.org/10.1109/mts.2021.3056293

Fidler, L. (2017). An Overview about the German Educational System. *Socialinis Ugdymas*, *45*(1), 104–107. https://doi.org/10.15823/su.2017.8

Grassini, S. (2023). Development and validation of the AI attitude scale (AIAS-4): a brief measure of general attitude toward artificial intelligence. *Frontiers in Psychology*, *14*. https://doi.org/10.3389/fpsyg.2023.1191628

Haenlein, M., & Kaplan, A. (2019). A Brief History of artificial intelligence: on the past, present, and future of artificial intelligence. *California Management Review*, *61*(4), 5–14. https://doi.org/10.1177/0008125619864925

Hasan, K. M. (2024). Quantitative methods in social science research: systematic review of content analysis, survey and experiment methodologies. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.4698175

Hornberger, M., Bewersdorff, A., & Nerdel, C. (2023). What do university students know about Artificial Intelligence? Development and validation of an AI literacy test. *Computers and Education Artificial Intelligence*, *5*, 100165. https://doi.org/10.1016/j.caeai.2023.100165

House of Lords source AI in the UK: ready, willing and able? (By Select Commitee on Artificial Intelligence & H. O. Lords). (2018). Authority of the House of Lords.

Jin, W. (2020). Research on machine learning and its algorithms and development. *Journal of Physics Conference Series*, *1544*(1), 012003. https://doi.org/10.1088/1742-6596/1544/1/012003

Kaplancali, U. T. (2017). Teaching Coding to Children: A Methodology for Kids 5+. *International Journal of Elementary Education*, *6*(4), 32. https://doi.org/10.11648/j.ijeedu.20170604.11

Kasinidou, M. (2023). Promoting AI Literacy for the Public. In *SIGCSE 2023: Proceedings of the 54th ACM Technical Symposium on Computer Science Education V. 2* (Vol. 2, p. 1237). Association for Computing Machinery (ACM). https://doi.org/10.1145/3545947.3573292

Kaur, A., Chen, W., & Oslo Metropolitan University. (2021). Exploring AI literacy among older adults [Journal-article]. *Oslo Metropolitan University*, 1. https://oda.oslomet.no/oda-xmlui/bitstream/handle/11250/3118891/AAATE2023.pdf?sequence=1

Kelly, J. (2025, April 25). *These jobs will fall first as AI takes over the workplace*. Forbes. https://www.forbes.com/sites/jackkelly/2025/04/25/the-jobs-that-will-fall-first-as-ai-takes-over-the-workplace/

Koc, N., & Celik, B. (2015). The impact of number of students per teacher on student achievement. *Procedia - Social and Behavioral Sciences*, *177*, 65–70. https://doi.org/10.1016/j.sbspro.2015.02.335

Kong, S., Cheung, W. M., & Zhang, G. (2021). Evaluation of an artificial intelligence literacy course for university students with diverse study backgrounds. *Computers and Education Artificial Intelligence*, *2*, 100026. https://doi.org/10.1016/j.caeai.2021.100026

Laitinen, A., & Sahlgren, O. (2021). AI systems and respect for human autonomy. *Frontiers in Artificial Intelligence*, *4*. https://doi.org/10.3389/frai.2021.705164

Long, D., Blunt, T., & Magerko, B. (2021). Co-Designing AI literacy exhibits for informal learning spaces. *Proceedings of the ACM on Human-Computer Interaction*, *5*(CSCW2), 1–35. https://doi.org/10.1145/3476034

Long, D., & Magerko, B. (2020). *What is AI literacy? Competencies and design considerations* (pp. 1–16). https://doi.org/10.1145/3313831.3376727

Lourduraj, J. C., Thangaraj, M., Sujatha, M., & Senthilkumar, S. (2024). An updated analysis of the application of artificial intelligence in everyday situations. *INTERANTIONAL JOURNAL OF SCIENTIFIC RESEARCH IN ENGINEERING AND MANAGEMENT*, *08*(07), 1–3. https://doi.org/10.55041/ijsrem36553

Lupton, D., & Williamson, B. (2017). The datafied child: The dataveillance of children and implications for their rights. *New Media & Society*, *19*(5), 780–794. https://doi.org/10.1177/1461444816686328

Macnamara, B. N., Berber, I., Çavuşoğlu, M. C., Krupinski, E. A., Nallapareddy, N., Nelson, N. E., Smith, P. J., Wilson-Delfosse, A. L., & Ray, S. (2024). Does using artificial intelligence assistance accelerate skill decay and hinder skill development without performers' awareness? *Cognitive Research Principles and Implications*, *9*(1). https://doi.org/10.1186/s41235-024-00572-8

Mai, J. (2016). Big data privacy: The datafication of personal information. *The Information Society*, *32*(3), 192–199. https://doi.org/10.1080/01972243.2016.1153010

Mamut, T. (2025, March 20). *AI will take your job. Get over it*. Fortune. https://fortune.com/2025/03/20/ai-jobs-displacement-careers-workforce/

Mariani, M. M., Perez-Vega, R., & Wirtz, J. (2021). AI in marketing, consumer research and psychology: A systematic literature review and research agenda. *Psychology and Marketing*, *39*(4), 755–776. https://doi.org/10.1002/mar.21619

McNulty, R. J., Gloeckler, L. C., & International Center for Leadership in Education. (2014). *Fewer, clearer, higher Common Core State Standards: Implications for students receiving special education services*. https://csaa.wested.org/wp-content/uploads/2019/11/Fewer-Clearer-Higher-Common-Core-State-Standards-Implications-for-Students-Receiving-Special-Education-Services.pdf

Ministerie van Algemene Zaken. (2021, June 4). *Subjects and attainment targets in primary education*. Primary Education | Government.nl. https://www.government.nl/topics/primary-education/subjects-and-attainment-targets-in-primary-education#:~:text=Dutch;,time%20to%20maths%20and%20science.

Ng, D. T. K., Leung, J. K. L., Chu, K. W. S., & Qiao, M. S. (2021). AI Literacy: definition, teaching, evaluation and ethical issues. *Proceedings of the Association for Information Science and Technology*, *58*(1), 504–509. https://doi.org/10.1002/pra2.487

Novatchkov, H., & Baca, A. (2013a, March 1). *Artificial intelligence in sports on the example of weight training*. https://pmc.ncbi.nlm.nih.gov/articles/PMC3761781/

Novatchkov, H., & Baca, A. (2013b, March 1). *Artificial intelligence in sports on the example of weight training*. https://pmc.ncbi.nlm.nih.gov/articles/PMC3761781/

Okemwa, K. (2024, May 8). Microsoft says most company execs won't hire anyone without an AI aptitude, prompting "a 142x increase in LinkedIn members adding AI skills like Copilot and ChatGPT to their profiles." *Yahoo Tech*. https://tech.yahoo.com/ai/articles/microsoft-says-most-company-execs-120001709.html

Paul, A. M. (2016). The coding revolution. *Scientific American*, *315*(2), 42–49. https://doi.org/10.1038/scientificamerican0816-42

Perella-Holfeld, F., Sallam, S., Petrie, J., Gomez, R., Irani, P., & Sakamoto, Y. (2024). Parent and educator concerns on the pedagogical use of AI-Equipped social robots. *Proceedings of the ACM on Interactive Mobile Wearable and Ubiquitous Technologies*, *8*(3), 1–34. https://doi.org/10.1145/3678556

Pinski, M., & Benlian, A. (2024). AI literacy for users – A comprehensive review and future research directions of learning methods, components, and effects. *Computers in Human Behavior Artificial Humans*, *2*(1), 100062. https://doi.org/10.1016/j.chbah.2024.100062

Primary and secondary education - Germany | Nuffic. (n.d.). Retrieved May 19, 2025, from https://www.nuffic.nl/en/education-systems/germany/primary-and-secondary-education#:~:text=Germany%20consists%20of%2016%20federal,%2Donline%20(in %20German).

Prunkl, C. (2024). Human Autonomy at Risk? An Analysis of the Challenges from AI. *Minds and Machines*, *34*(3), 5. https://doi.org/10.1007/s11023-024-09665-1

Raji, N. E., Ijomah, N. T. I., & Eyieyien, N. O. G. (2024). Data-Driven decision making in agriculture and business: The role of advanced analytics. *Computer Science & IT Research Journal*, *5*(7), 1565–1575. https://doi.org/10.51594/csitrj.v5i7.1275

Ross, E. W., Mathison, S., & Vinson, K. D. (2014). Social Studies Education and Standards-Based Education Reform in North America: Curriculum Standardization, High-Stakes Testing, and Resistance. *Revista Latinoamericana De Estudios Educativos (Colombia)*, *10*(1), 19–48. https://www.redalyc.org/pdf/1341/134139791002.pdf

Saatci, E. (2025). AI and Ethics: Scale Development for Measuring Ethical Perceptions of Artificial Intelligence Across Sectors and Countries. *International Journal of Economic Behavior and Organization*, *13*(1), 35–50. https://doi.org/10.11648/j.ijebo.20251301.14

Senn, G. J., McMurtrie, D. H., & Coleman, B. K. (2013). RAFTing with raptors: Connecting science, English language arts, and the Common Core State Standards. *Middle School Journal*, *44*(3), 52–55. https://doi.org/10.1080/00940771.2013.11461855

Seya, K., Kobayashi, N., & Shirasaka, S. (2020). Teaching Method for Non-technical Adult Learners to Gain an Authentic Understanding of AI within a Day. *Information Engineering Express*, *6*(1), 14–26. https://doi.org/10.52731/iee.v6.i1.523

Sharma, I., Kumar, P., & Kaushik, R. (2022). Application of AI in everyday life. *Industrial Engineering Journal*, *51*(09), 33–38. https://doi.org/10.36893/iej.2022.v51i9.033-038

Sidhu, B. K. (2025). Hallucinations in Artificial intelligence: origins, detection, and mitigation. *International Journal of Science and Research (IJSR)*, *14*(1), 8–15. https://doi.org/10.21275/sr241229170309

Tavakol, M., & Dennick, R. (2011). Making sense of Cronbach's alpha. *International Journal of Medical Education*, *2*, 53–55. https://doi.org/10.5116/ijme.4dfb.8dfd

The Dutch school system. (2025, April 10). The Hague International Centre. https://www.thehagueinternationalcentre.nl/the-dutch-school-system

Touretzky, D., Gardner-McCune, C., Martin, F., & Seehorn, D. (2019). Envisioning AI for K-12: What Should Every Child Know about AI? *Proceedings of the AAAI Conference on Artificial Intelligence*, *33*(01), 9795–9799. https://doi.org/10.1609/aaai.v33i01.33019795

Vico, F., Molina, M., Orden, D., Ortiz, J., García, R., & Masa, J. (2019). A Coding Curriculum for K-12 Education: The Evidence-Based Approach. *EDULEARN Proceedings*, *1*, 7102–7106. https://doi.org/10.21125/edulearn.2019.1698

Vorobeva, D., Fassi, Y. E., Pinto, D. C., Hildebrand, D., Herter, M. M., & Mattila, A. S. (2022). Thinking Skills Don't Protect Service Workers from Replacement by Artificial Intelligence. *Journal of Service Research*, *25*(4), 601–613. https://doi.org/10.1177/10946705221104312

Wisniewski, P., Ghosh, A. K., Xu, H., Rosson, M. B., & Carroll, J. M. (2017). *Parental Control vs. Teen Self-Regulation*. Association for Computing Machinery. https://doi.org/10.1145/2998181.2998352

Wong, G. K. W., Ma, X., Dillenbourg, P., & Huan, J. (2020). Broadening artificial intelligence education in K-12. *ACM Inroads*, *11*(1), 20–29. https://doi.org/10.1145/3381884

Xu, Y., Branham, S., Deng, X., Collins, P., & Warschauer, M. (2021). *Are current voice interfaces designed to support children's language development?* (pp. 1–12). Association for Computing Machinery. https://doi.org/10.1145/3411764.3445271

Yadav, P., Yadav, A., & Agrawal, R. (2022). Use of artificial intelligence in the real world. *International Journal of Computer Science and Mobile Computing*, *11*(12), 83–90. https://doi.org/10.47760/ijcsmc.2022.v11i12.008

Yu, Y. (2024). Safeguarding Children in Generative AI: Risk Frameworks and Parental Control Tools. *ACM Digital Library*, 121–123. https://doi.org/10.1145/3688828.3699656

Zhang, Z., Xu, Y., Wang, Y., Yao, B., Ritchie, D., Wu, T., Yu, M., Wang, D., & Li, T. J. (2022). StoryBuddy: A Human-AI Collaborative Chatbot for Parent-Child Interactive Storytelling with Flexible Parental Involvement. *CHI Conference on Human Factors in Computing Systems*, 1–21. https://doi.org/10.1145/3491102.3517479

Zhou, X., & Schofield, L. (2024). Developing a conceptual framework for Artificial Intelligence (AI) literacy in higher education. *Journal of Learning Development in Higher Education*, *31*. https://doi.org/10.47408/jldhe.vi31.1354

Appendix A

Pre-testing Interview Guide

Introduction to Interview

This interview will be conducted in order to test how relevant the topics of the study's survey are to the opinions of parents in regards to including AI into the standardized educational system. If at any moment you feel uncomfortable, you may stop the interview. Respond freely to the following questions.

Questions

1. How would you define AI literacy?
2. Can you come up with some applications of AI in the real-world setting?
3. Can you explain how AI works?
4. What are some ethical concerns that are often mentioned when it comes to AI?
    a. How concerned are you about the topics just mentioned?
5. Is AI safe?
6. What is your attitude towards AI?
7. How important is AI literacy to you?
8. Do you support schools in adding AI literacy to education?

Appendix B

Survey English

The following survey will look into the AI literacy of parents and their opinions towards AI, especially when it comes to adding AI into the standardized education system.

Demographic question:

The following questions are general non-identifying demographic questions that allow for understanding of the participant's backgrounds.

1. What is your age?
2. What is your gender?
3. What is your current country of residence?
4. How many children do you have?
5. What is the highest level of education of your children?

AI Literacy Questions:

This next section looks at your understanding and knowledge of artificial intelligence. Please seek out the correct answer to each question to the best of your ability.

1. AI Concepts: understand AI and its origins (ex. deep learning)
2. AI Applications: how it can be used in the real world
3. AI Ethics and Safety: ethical challenges and safety concerns of AI

In which of these areas is AI typically applied?	- ***Detecting credit card fraud** - Cryptocurrency mining -Web tracking - Encryption for instant messaging services
Which of the following systems often use AI?	-Flight surveillance systems -Geopositioning systems -3D printing systems **-*Inventory management systems**
How do AI systems make decisions?	- ***based on mathematical-logical principles** - based on links defined by programmers - based on quantum entanglement - based on artificial intuition
What is a key criterion for the quality of a model in machine learning?	**- *it can predict the output values of the test data as well as possible** - it contains as few variables as possible - it is as well adapted as possible to the training data - the predictions are as unambiguous as possible
Which societal challenge is frequently mentioned in the context of AI?	- lack of investment incentives in the educational system

	- chip shortage in industry due to the high computational cost of AI - high error rate in AI-enabled manufacturing **- *replacement of human workforce by AI**
What are central risks in using AI for predictive policing?	- Vulnerability to hacking **- *Discrimination against suspects based on origin and status** - Lack of legal certainty in the event of AI breakdown - Undermining the authority of police officers

The next three sections will look into your opinions and sentiments towards AI in several regards. Please indicate how much you agree or disagree to each statement.

Level of Concern: five-point Likert scale

1. AI systems are regularly audited to ensure that human intervention can override AI decisions if necessary.
2. AI systems are tested for fairness before deployment.
3. AI systems ensure that user data is anonymized where applicable.
4. I trust the decision-making process of AI systems.
5. AI systems comply with national and international data protection regulations.
6. Discrimination through AI is prevented through regular system audits.

Attitude towards AI: five-point Likert Scale

1. I believe that AI will improve my life.
2. I believe that AI will improve my work.
3. I think I will use AI technology in the future.
4. I think AI technology is a threat to humans (reverse item).
5. I think AI technology is positive for humanity.

Support for AI literacy being added into educational systems: five-point Likert Scale

1. I believe AI literacy should be included in standardized education.
2. An increased AI literacy will provide an advantage when applying for jobs.
3. AI literacy is as important as other grade school subjects.
4. It is important for children to understand how to use and navigate AI tools.

Thank you for taking the time to contribute to this survey.

If any questions or concerns arise, please the following email is available for contact.

s.nase@student.utwente.nl

Appendix C

Survey German

Die folgende Umfrage untersucht die KI-Kompetenz von Eltern sowie ihre Meinungen gegenüber KI, insbesondere im Hinblick auf die Integration von KI in das standardisierte Bildungssystem.

Demographic question:

Die folgenden Fragen sind allgemeine, nicht personenbezogene demografische Fragen, die dazu dienen, den Hintergrund der Teilnehmenden besser zu verstehen.

1. Wie alt sind Sie?
2. Was ist Ihr Geschlecht?
3. In welchem Land wohnen Sie derzeit?
4. Wie viele Kinder haben Sie?
5. Welchen hoesten Buldungsabschluss haben Ihre Kinder erreicht?

Fragen zur KI-Kompetenz:

Im nächsten Abschnitt geht es um Ihr Verständnis und Wissen über Künstliche Intelligenz. Bitte versuchen Sie, jede Frage so gut wie möglich korrekt zu beantworten.

1. KI-Konzepte: Verstehen con KI und Ihrer Urspuenge (z.B. Deep Learning)
2. KI-Anwendungen: Nutzungsmoeglichkeiten von KI in der realen Welt.
3. KI-Ethik und Sicherheit: Ethische Herausforderungen und Sicherheitsbedenken im Zusammenhang mit KI

In welchen diser Bereiche wird KI typischerweise eingesetzt?	- **Erkennung von Kreditkartenbetrug** - Kryptowährungs-Mining - Web-Tracking - Verschlüsselung für Instant-Messaging-Dienste
Welche der folgenden Systeme verwenden häufig KI?	- Flugüberwachungssysteme - Geopositionssysteme - 3D-Drucksysteme **- Bestandsmanagementsysteme**
Wie treffen KI-Systeme Entscheidungen?	**- Basierend auf mathematisch-logischen Prinzipien** - Basierend auf Verknüpfungen, die von Programmierern definiert wurden - Basierend auf Quantenverschränkung - Basierend auf künstlicher Intuition
Was ist ein zentrales Kriterium für die Qualität eines Modells im maschinellen Lernen?	**- Es kann die Ausgabewerte der Testdaten möglichst gut vorhersagen** - Es enthält möglichst wenige Variablen - Es ist möglichst gut an die Trainingsdaten angepasst - Die Vorhersagen sind möglichst eindeutig

Welche gesellschaftliche Herausforderung wird häufig im Zusammenhang mit KI genannt?	- Fehlende Investitionsanreize im Bildungssystem - Chipmangel in der Industrie aufgrund der hohen Rechenkosten von KI - Hohe Fehlerquote in der KI-gestützten Fertigung **- Ersetzung menschlicher Arbeitskräfte durch KI**
Was sind zentrale Risiken beim Einsatz von KI für Predictive Policing?	- Anfälligkeit für Hackerangriffe **- Diskriminierung von Verdächtigen aufgrund ihrer Herkunft und ihres Status** - Fehlende Rechtssicherheit bei einem Ausfall von KI - Untergrabung der Autorität von Polizeibeamten

In den nächsten drei Abschnitten werden Ihre Meinungen und Einstellungen gegenüber KI in verschiedenen Bereichen untersucht. Bitte geben Sie an, inwieweit Sie den jeweiligen Aussagen zustimmen oder nicht zustimmen.

Besorgnisniveau: Fünf-Punkte-Likert-Skala

1. KI-Systeme werden regelmäßig geprüft, um sicherzustellen, dass menschliches Eingreifen Entscheidungen von KI-Systemen bei Bedarf übersteuern kann.
2. KI-Systeme werden vor dem Einsatz auf Fairness getestet.
3. KI-Systeme gewährleisten, dass Nutzerdaten, wo anwendbar, anonymisiert werden.
4. Ich vertraue dem Entscheidungsprozess von KI-Systemen.
5. KI-Systeme halten nationale und internationale Datenschutzvorschriften ein.
6. Diskriminierung durch KI wird durch regelmäßige Systemprüfungen verhindert.

Einstellung gegenüber KI: Fünf-Punkte-Likert-Skala

1. Ich glaube, dass KI mein Leben verbessern wird.
2. Ich glaube, dass KI meine Arbeit verbessern wird.
3. Ich denke, dass ich in Zukunft KI-Technologien nutzen werde.
4. Ich denke, dass KI-Technologie eine Bedrohung für den Menschen darstellt (umgekehrter Punkt).
5. Ich denke, dass KI-Technologie positiv für die Menschheit ist.

Unterstützung für die Integration von KI-Kompetenz in Bildungssysteme: Fünf-Punkte-Likert-Skala

1. Ich bin der Meinung, dass KI-Kompetenz in die standardisierte Bildung aufgenommen werden sollte.
2. Eine erhöhte KI-Kompetenz wird bei Bewerbungen einen Vorteil verschaffen.
3. KI-Kompetenz ist genauso wichtig wie andere Schulfächer.
4. Es ist wichtig, dass Kinder verstehen, wie sie KI-Werkzeuge verwenden und navigieren können.

Vielen Dank, dass Sie sich die Zeit genommen haben, an dieser Umfrage teilzunehmen.
Bei Fragen oder Anliegen können Sie sich gerne an die folgende E-Mail-Adresse wenden:
s.nase@student.utwente.nl

Appendix D

Survey Dutch

De volgende enquête onderzoekt de AI-geletterdheid van ouders en hun mening over AI, vooral met betrekking tot de integratie van AI in het gestandaardiseerde onderwijssysteem.

Demografische vragen:

De volgende vragen zijn algemene, niet-identificerende demografische vragen die bedoeld zijn om meer inzicht te krijgen in de achtergrond van de deelnemers.

1. Wat is uw leeftijd?
2. Wat is uw geslacht?
3. Wat is uw huidige woonland?
4. Hoeveel kinderen heeft u?
5. Wat is het hoogste opleidingsniveau van uw kinderen?

Vragen over AI-geletterdheid:

In het volgende gedeelte gaat het om uw begrip en kennis van kunstmatige intelligentie. Probeer elke vraag zo goed mogelijk correct te beantwoorden.

1. AI-concepten: begrijpen van AI en zijn oorsprong (bijv. deep learning)
2. AI-toepassingen: hoe AI in de echte wereld kan worden gebruikt
3. AI-ethiek en -veiligheid: ethische uitdagingen en veiligheidszorgen omtrent AI

In welke van deze gebieden wordt AI typisch toegepast?	**- Opsporen van creditcardfraude** - Mijnbouw van cryptocurrency - Webtracking - Encryptie voor instant messaging-diensten
Welke van de volgende systemen maken vaak gebruik van AI?	- Vluchtbewakingssystemen - Geopositioneringssystemen - 3D-printsystemen **- Voorraadbeheersystemen**
Hoe nemen AI-systemen beslissingen?	**- Gebaseerd op wiskundig-logische principes** - Gebaseerd op verbanden gedefinieerd door programmeurs - Gebaseerd op kwantumverstrengeling - Gebaseerd op kunstmatige intuïtie
Wat is een belangrijk criterium voor de kwaliteit van een model in machine learning?	**- Het kan de uitvoerwaarden van de testgegevens zo goed mogelijk voorspellen** - Het bevat zo min mogelijk variabelen - Het is zo goed mogelijk aangepast aan de trainingsgegevens - De voorspellingen zijn zo eenduidig mogelijk

Welke maatschappelijke uitdaging wordt vaak genoemd in de context van AI?	- Gebrek aan investeringsprikkels in het onderwijssysteem - Chiptekort in de industrie door de hoge rekenkosten van AI - Hoge foutenmarge bij AI-ondersteunde productie **- Vervanging van menselijke arbeid door AI**
Wat zijn centrale risico's bij het gebruik van AI voor voorspellende politiewerkzaamheden?	- Kwetsbaarheid voor hacking **- Discriminatie van verdachten op basis van afkomst en status** - Gebrek aan juridische zekerheid bij een AI-storing - Ondergraving van het gezag van politieagenten

In de volgende drie secties worden uw meningen en gevoelens ten opzichte van AI in verschillende opzichten onderzocht. Geef alstublieft aan in hoeverre u het eens of oneens bent met elke stelling.

Niveau van bezorgdheid: vijfpuntsschaal (Likert-schaal)

1. AI-systemen worden regelmatig gecontroleerd om ervoor te zorgen dat menselijke tussenkomst AI-beslissingen kan overrulen indien nodig.
2. AI-systemen worden getest op eerlijkheid vóór implementatie.
3. AI-systemen zorgen ervoor dat gebruikersgegevens, waar van toepassing, worden geanonimiseerd.
4. Ik vertrouw op het besluitvormingsproces van AI-systemen.
5. AI-systemen voldoen aan nationale en internationale regelgeving voor gegevensbescherming.
6. Discriminatie door AI wordt voorkomen door regelmatige systeemaudits.

Houding tegenover AI: vijfpuntsschaal (Likert-schaal)

1. Ik geloof dat AI mijn leven zal verbeteren.
2. Ik geloof dat AI mijn werk zal verbeteren.
3. Ik denk dat ik in de toekomst AI-technologie zal gebruiken.
4. Ik denk dat AI-technologie een bedreiging vormt voor de mens (omgekeerd item).
5. Ik denk dat AI-technologie positief is voor de mensheid.

Ondersteuning voor het opnemen van AI-geletterdheid in onderwijssystemen: vijfpuntsschaal (Likert-schaal)

1. Ik geloof dat AI-geletterdheid opgenomen moet worden in het gestandaardiseerde onderwijs.
2. Een toegenomen AI-geletterdheid biedt een voordeel bij het solliciteren naar banen.
3. AI-geletterdheid is net zo belangrijk als andere vakken op de basisschool.

4. Het is belangrijk dat kinderen begrijpen hoe ze AI-tools kunnen gebruiken en navigeren.

Bedankt dat u de tijd heeft genomen om aan deze enquête deel te nemen.
Mocht u vragen of opmerkingen hebben, dan kunt u contact opnemen via het volgende e-mailadres:
s.nase@student.utwente.nl

Appendix E

AI Statement

AI applications were used alongside the writing of this thesis. No generative AI was copied into this thesis; everything was written by the researcher. Grammarly was used for sentence correction and spelling fixes. Scribbr was used for citation generation. ChatGPT was used to translate the surveys from English into Dutch and German.