Global Adoption of AI in Education: Insights from a Meta-Analysis across Countries

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Abstract

Following recent surveys by Forbes, Microsoft, and IPSOS, AI technologies are increasingly being introduced as a step towards enhancing teaching and learning. However, a holistic examination of the main factors affecting the acceptance and use of AI in education is necessary. Specifically, we tested three hypotheses using three models in meta-analysis to deeply understand about the impact of AI in education and learning. We developed a model explains a significant portion of the variance in AI understanding, showcasing the transformative role AI plays in modern education systems. The developed risk model assessed the impact of AI technology based on responses from 19,504 individuals, using data from 2022 across twenty-eight countries on five continents. AI's integration may accelerate the decline of traditional educational institutions, paving the way for technologically advanced and efficient alternatives Cross-national collaboration and sharing best practices are essential to address variability and ensure equitable access to AI-driven education. This study provides a foundation for evidence-based policies to reimagine education as inclusive, adaptive, and future-ready in the AI era. Improving educational learning development significantly enhances AI literacy, highlighting the need for investments in educational resources and modern curricula. The number of educational institutions and historical timelines are less important than the quality and relevance of education. AI-driven platforms are likely to reduce the need for traditional educational institutions, emphasizing the shift towards personalized, technology-integrated learning environments.The research demonstrates originality by exploring the significant impact of educational learning development on AI literacy, a relatively underexplored area. It challenges conventional assumptions by showing that the number of educational institutions and historical timelines are less critical than the quality of education.

Key Words: AI Understanding, Education, Learning, Cross-countries, Educational Institutions.

Paper Type – Research paper

1. Introduction

The relationship between education and human understanding of artificial intelligence (AI) is crucial in fostering a resilient population that is able to adapt to technological advances (CANTAŞ, et al. 2024; López-Chila et al. 2024; Walter, 2024). As AI increasingly permeates industries, economies, and human daily lives, it is essential to educate individuals with fundamental knowledge about how AI can be used and applied and the implications of its use. Research shows that countries with advanced education systems tend to demonstrate a broader understanding of AI technologies (Aziz et al. 2024; Chan, 2023; Alshorman, 2024). For example, integrating digital literacy, data science, and AI concepts into school curricula can create a workforce better prepared to address the challenges and opportunities of AI. Beyond the workforce, educated populations are more likely to participate in public discourse, engage with the ethical and social implications of AI, and help shape policy, shaping responsible approaches to AI development (Tegmark, 2017). Therefore, an educational strategy is essential to maximize the benefits of AI while minimizing its risks to society.

There have been several surveys conducted to understand the impact of AI on education. Here are a few notable ones: Forbes Advisor Survey (October 2023) involved 500 practicing educators from around the U.S. and explored their experiences with AI in the classroom. It revealed that more than half of the teachers believe AI has had a positive effect on teaching and learning. The survey also highlighted the most common AI tools used, such as AI-powered educational games, adaptive learning platforms, and automated grading systems. The second one is Microsoft AI in Education Report (April 2024) surveyed educators, academic and IT leaders, and students from K-12 schools and higher education institutions. The survey focused on their perceptions, familiarity, uses, and concerns around AI tools. One key finding was that 47% of education leaders use AI every day. The last one is Educator Confidence Report (November 2024) based on responses from over 1,200 educators, discussed the evolving challenges and opportunities in education, including the growing role of digital technologies and generative AI in transforming classrooms (Houghton Mifflin Harcourt., 024). These surveys provide valuable insights into how AI is being integrated into educational settings and its perceived impact on teaching and learning.

Artificial intelligence (AI) and information management systems are playing a transformative role in modern education by enhancing learning experiences and administrative efficiency (Arora, and Bhardwaj, 2022; Kerimbayev et al. 2023). By leveraging vast datasets, AI enables the development of personalized learning paths tailored to student needs and preferences. Such adaptive learning environments, where content and pace are adjusted in real time, overcome the limitations of one-size-fits-all instructional models and significantly improve student engagement and knowledge retention. In addition, AI automates administrative tasks in education such as grading, scheduling, and progress tracking, allowing educators to devote more time to innovation and creativity in education and research and foster meaningful student interactions. This synergy between AI and information management not only increases efficiency (Huang et al, 2021), but also has broad implications for access and equity, making quality education more scalable and inclusive. By streamlining these processes, AI helps create an education system that is better equipped to respond to diverse and rapidly evolving societal needs (Pellas, 2023).

AI can create a strong link between information management and the educational standards of a society (Vergara et al. 2024; Wang et al.,2021; 2024). Research indicates that integrating artificial intelligence (AI) into learning management systems can enhance educational standards by enabling adaptive learning, personalized experiences, and active engagement (Oancea, et al. 2023; Demir, 2024). AI improves access to and management of educational data, allowing institutions to create equitable and efficient learning environments aligned with societal educational goals. Additionally, AI promotes self-regulated learning and supports open educational resources, linking information management to educational development (Abimbola et al, 2024). By analyzing large datasets on students' learning styles, strengths, and weaknesses, AI can personalize learning pathways and recommend tailored resources, leading to more effective learning and improved outcomes. Furthermore, AI-based systems provide personalized feedback, guidance, and targeted instruction, adapting to students' pace and style to address specific learning needs. These systems complement traditional teaching methods and expand access to quality education. Lastly, AI automates assessment and grading, freeing educators to focus on individualized instruction and meaningful student interaction.

Automated learning systems can provide objective and consistent learning objectives, efficient grading, reduce the risk of misclassification, and increase the fairness of educational assessments (Huang et al., 2024). This allows educators to focus more on developing innovative curriculum and engaging students in practice, and align teaching practices with evolving information landscapes. In addition, AI algorithms can recommend tailored learning resources such as articles, videos, and interactive simulations based on students' learning goals and interests. This helps students access high-quality information and expand their knowledge beyond the traditional curriculum, bridging the gap between formal education and the vast array of online information (Ahn, 2024). In addition, these systems strengthen information literacy and critical thinking skills. AI can also identify students at risk of academic failure by collecting big data such as videos of behavior in the educational environment and at home. By analyzing performance data, AI can predict which students are likely to struggle and alert teachers or administrators, enabling timely and targeted assistance (Rastrollo-Guerrero, 2020). This proactive approach can prevent students from falling behind and significantly improve overall educational outcomes.

Does the adoption of artificial intelligence (AI) in education have the potential to change the landscape of educational institutions? These changes include streamlining administrative tasks, reducing human resources in educational settings, and reducing the need for large physical campuses and centralized learning infrastructure. As a result, some traditional institutions may consolidate or transition to hybrid models that more broadly integrate AI and digital platforms. AI's ability to personalize instruction and provide real-time feedback could decentralize learning and shift the focus from institution-based learning to more student-centered and distributed models. Similarly, Holmes et al. 2019) argue that AI can expand access to quality education globally, potentially reducing the need for local institutions in areas where physical infrastructure was once a barrier. As a result, while AI can democratize education and make it more accessible, it may also lead to fewer traditional educational institutions as learning becomes more virtual and customized.

Given the significant advances in artificial intelligence (AI) in developed and developing countries, in particular, there is limited research on how the year of a country's independence affects the number and distribution of educational institutions and how these factors influence the implementation and effectiveness of AI-based educational tools and systems. Whether countries that achieved national independence early are ahead in the use of AI is an intuitive research gap question because it may ignore the historical, socio-political, and infrastructural contexts that shape educational landscapes. Addressing this gap could provide valuable insights into the adaptation of AI solutions to improve educational outcomes in different settings and ensure that AI technologies are not tied to nations' pasts.

While there is limited direct research that examines the relationship between the number of educational institutions and a country's year of independence, some studies show that a country's educational development is influenced by its historical and political context, including the time of independence (Ranganath, 2021). For example, countries that gained independence earlier may have had more time to build strong educational systems, while countries that have become more independent recently may face challenges in rapidly developing their infrastructure, including educational institutions (Santiago et al., 2012). However, this relationship is complex because factors such as political stability, economic development, and government policies also play an important role in shaping education systems.

In this study, the impact of artificial intelligence, educational development, and people's future outlook relative to the year of independence of that country. The number of educational institutions can inspire the adjustment of information strategies and knowledge transfer and decision-making in organizations and governments in different societies and improve the strategic vision of education in different countries. This research can provide insights into optimizing human capital, improving the efficiency of education budgets through informed strategies, and fostering innovation through the effective use of information assets. By examining the interplay of these elements, educational activities can gain competitive advantage in an evolving information landscape.

The rest of this paper begins with a review of literature focusing on the interrelationship between artificial intelligence, educational development, the number of educational institutions, and the year of independence of the countries studied. Next, the research questions and assumptions are presented. The methodology section explains the data, variables, and statistical methods used for data analysis. Finally, the paper concludes with a discussion of the results and the conclusion.

2. Theoretical Background

The global AI in education market, valued at $2.5 billion in 2022, is projected to reach $6 billion by 2030. Nearly 44% of children are actively engaged with generative AI, with more than half (54%) using it to complete school and homework assignments. AI integration is also common among educators, with 60% of teachers incorporating AI into their daily teaching practices. The most common AI tools used by teachers are AI-based educational games, which 51% use. In primary education (K-12), virtual learning platforms such as Google Classroom are very popular, with 80% of teachers using them at least once a week. Additionally, 39% of students are exploring generative AI out of curiosity, while 53% of higher education students are using AI to create content for graded assignments. However, incidents of cheating related to AI were reported by 24.11% of charter high school students, compared to 6.44% in private high schools and 15.2% in public institutions. Despite these challenges, 51% of teachers believe that AI will have a positive impact on student learning and progress, while 21% have negative views. Among students, 34% see AI as beneficial for education, while 20% see it as negative (AIPRM, 2024).

2.1. Educational Theories and AI

In this section, we explore theories about the use of AI in education, especially from a constructivist viewpoint. Constructivist theory posits that learners actively build knowledge through their experiences and interactions with their surroundings (Narayan et al., 2013; Phillips, 2015; Driscoll, 2000). AI can enhance this learning process by providing personalized experiences that cater to individual needs and learning styles. For instance, AI tutors can offer customized feedback and guidance, supporting learning based on the learner's current level of understanding (Koedinger and Aleven, 2016).

Constructivism emphasizes the importance of play and exploration, and AI can promote this by creating interactive simulations and virtual environments where learners can experiment and uncover knowledge. Furthermore, AI can facilitate collaborative learning by connecting students with peers and experts, encouraging the shared construction of knowledge. By analyzing learner data, AI systems can pinpoint knowledge gaps and suggest resources that challenge learners to deepen their understanding, fostering deeper learning and higher-order thinking skills (Benfarha and Lamarti, 2023; Gligorea et al., 2033; Das, 2023).

AI's capacity to personalize, adapt, and encourage interaction aligns with constructivist principles, potentially transforming education into a more learner-centered and effective experience (Schunn, 2020). In this context, AI can greatly improve educational growth by providing tailored practice and feedback. AI-powered learning platforms can offer tailored exercises and quizzes that modify in difficulty according to each student's performance, providing instant feedback on their responses. This method aids in strengthening accurate answers and swiftly correcting errors, enabling students to progress at their own speed and fully grasp concepts through ongoing practice and reinforcement.

Cognitive load theory suggests that learning is most effective when the need for working memory is minimized. When we look at the role of AI in education through the lens of cognitive load theory, we can see several significant benefits. AI has the ability to adapt educational materials to meet the unique needs of each student, breaking down complex information into smaller, more digestible chunks, and providing support where needed (van Merenboer & Soler, 2005). By customizing how information is presented and the speed at which it is presented, AI helps reduce cognitive load, thereby improving comprehension and memory. In addition, AI-based tools can provide immediate feedback and assistance, which reduces the mental effort required to understand new concepts and allows students to focus more effectively on deeper learning goals. However, there is a risk that overreliance on AI in education can reduce critical thinking and problem-solving abilities. If students rely heavily on AI for personal assistance, they may find it challenging to cope with learning situations that require independent thinking and cognitive power. Furthermore, if AI systems are not user-friendly or if students have to repeatedly switch between different AI tools and traditional learning methods, it can unintentionally increase the learning load. It is essential to ensure that AI acts as a complement, rather than a replacement, for traditional teaching methods to avoid these issues.

AI can act as an online tutor, providing tailored feedback and customized learning experiences that help students increase their understanding and enable them to progress beyond their existing skills. This personalized approach can be tailored to each student's unique learning pace and preference, resulting in improved skills and knowledge. However, there are several potential drawbacks. AI, lacking human empathy, may not be able to properly assess a student's emotional state or motivation, both of which are essential for successful learning (Cardona, et al. 2023). Overreliance on AI may reduce human interaction, which is critical for fostering social skills and collaborative learning. Furthermore, if access to AI-based educational resources is not widespread, it may exacerbate existing inequalities and disadvantage certain students. Achieving harmony between the integration of AI and conventional educational techniques, while ensuring equitable access, is crucial to optimizing the benefits of AI in education (Walter, 2024).

Based on Bloom's Taxonomy theory, learning objectives in education can be categorized into six levels: remembering, understanding, applying, analyzing, evaluating, and creating (Bloom et al, 1956; Krathwohl, 2002; Anderson and Krathwohl, 2001). From this perspective, AI has the potential to greatly improve educational outcomes by addressing different cognitive levels. AI-based educational tools can provide personalized learning experiences that adapt to each student's current understanding and pace, thereby supporting essential skills such as remembering and understanding. For example, AI can provide customized tests and real-time feedback, helping students grasp essential concepts and facts. At higher levels of thinking, AI can promote deeper learning by presenting complex problem-solving scenarios, encouraging critical analysis, and fostering creativity through adaptive learning platforms. However, there are some drawbacks. AI may not be able to fully replicate the subtle human guidance needed to develop higher-order thinking skills such as evaluation and creation. These skills often require contextual understanding, empathy, and the ability to inspire and engage students – qualities that AI lacks. Furthermore, over-reliance on AI can reduce opportunities for collaborative learning and peer interaction that are critical for holistic development. There is also concern that AI tools could widen the educational gap if they are not available to all students (Hamoud & Shaqur, 2024). Therefore, while AI offers significant benefits, it should currently serve as a complement, not a replacement, to human educators, ensuring a balanced approach to developing cognitive skills in Bloom's Taxonomy.

Artificial intelligence can serve as a potent tool by emphasizing learning as a process of forming networks and connections, according to connectivism theory (PLUEGER, C. T. 2024). AI can aid in this by offering tailored learning paths, flexible content, and immediate feedback. Artificial intelligence has the capability to examine vast quantities of data to recognize trends and recommend resources, aiding students in developing and broadening their knowledge networks. Platforms powered by AI can link learners with peers, teachers, and experts globally, promoting collaborative learning and the exchange of knowledge. This aligns perfectly with connectivism's focus on the significance of communication and learning through networks. Nevertheless, there are possible disadvantages. Excessive dependence on artificial intelligence may result in a disjointed learning experience if it is not effectively incorporated into the larger educational system. The absence of human interaction and emotional intelligence within artificial intelligence can impede the cultivation of soft skills and critical thinking, both of which are crucial in connectivism. Moreover, the success of artificial intelligence in promoting effective communication relies on the quality of the data and algorithms employed. Incorrect or biased information can result in misinformation and perpetuate current inequalities. Consequently, although AI provides considerable advantages in improving connectivity and individualized education, it needs to be utilized carefully and with human oversight to fully realize its advantages (Siemens, 2022).

2.2. Education: countries and continents

Educational advancement differs greatly among various nations and regions because of several factors, such as financial resources, cultural principles, governmental regulations, and historical backgrounds (World Bank, 2024). In certain areas, education systems receive substantial funding and focus on technology and innovation, offering students access to advanced resources and educational opportunities. On the other hand, in certain regions, educational institutions might face challenges due to restricted funding, obsolete resources, and inadequate infrastructure, potentially affecting the quality of education. Moreover, cultural perspectives on education, including the emphasis on traditional schooling compared to vocational education, can influence educational focuses and results (Teräs, 2019). These differences underscore the significance of customized educational approaches that cater to the distinct needs and obstacles of every area to foster fair and efficient learning experiences globally.

There are many varying aspects that either enhance or obstruct the educational advancement of a campaign, (Dodiya, 2018) which some of which may include: First, there is enough funds to develop education material, build schools, and pay teachers; all of which in one way or the other have direct implications on quality of education. Second, good education policies including policies on curricular, teacher education policies, investment in technology are necessary ingredients for a strong education system. Third, and equally important, are the direction in which society and culture ascribes values taking to education. For instance, in the societies that emphasis education, students are less likely to lack motivation and support. Fourthly, Quality of teachers and indeed quality of education is remained to those who are well trained, motivated, and paid well. Fifthly, seeking to address the educational needs and technology and exposure to extracurricular activities has a means of widening the scope of learning. Sixth, provision of safe and adequate schools enhances the learning experience. Seventh, parents supporting their children in the learning have proven to make their educational development much better than those who are not. Eighth, effective students whose dietary requirements are met are likely to achieve more in the process of learning than their counterparts. Ninth, good political will and governance stresses that there is constant and steady orientation to the practice of education.

Educational development differs greatly across continents due to various socio-economic conditions, government policies, and cultural influences. In Africa, numerous countries encounter obstacles such as limited resources, high dropout rates, and gender inequalities, although there are ongoing efforts to enhance access and quality (Huang 2024, UNESCO, 2021). Asia presents a broad spectrum of educational outcomes, with nations like South Korea and Japan performing exceptionally well in global rankings, while others, especially in South Asia, continue to face challenges with basic literacy and school attendance (World Bank, 2020). Europe typically enjoys high educational standards, supported by strong government initiatives and comprehensive systems, though disparities exist between Western and Eastern Europe (European Commission, 2019). In North America, both the United States and Canada have solid educational frameworks, but issues like inequality and differing state policies can impact overall consistency (OECD, 2020). South America has made notable progress in boosting enrollment and literacy rates, yet quality and access still vary, particularly in rural regions (UNICEF, 2021). Australia and New Zealand uphold high educational standards, focusing on inclusivity and innovation (Australian Government, 2020).

2.3 Supply of Educational Institutions

The quantity of educational institutions within a nation greatly affects society's comprehension and acceptance of AI knowledge. A greater number of institutions usually results in increased chances for people to obtain education and training in AI, producing a better-informed and more skilled populace. These organizations can provide targeted courses, research initiatives, and workshops centered around AI, thus promoting a culture of innovation and analytical thinking. Furthermore, educational organizations frequently partner with industries and government agencies to create AI programs that align with current technological developments, ensuring students are adequately prepared for employment (Smith & Anderson, 2020). This extensive educational framework can clarify AI, rendering it more approachable and less daunting for the general population, which can subsequently promote social acceptance and assimilation of AI technologies. Thus, a strong network of educational establishments can significantly influence the development of a society that understands and can utilize AI for multiple purposes (Brown, 2021).

2.4. Education and Independence Year

Historical Institutionalism (HI) theory highlights the significance of temporal sequences, path dependencies, and critical junctures in influencing institutional cange, particularly within education systems. HI indicates that the historical environment and the timing of major occurrences greatly affect the evolution and stability of educational institutions. For instance, nations with a lengthy tradition of stable governance and a focus on education usually possess more resilient educational systems. Several instances exist of nations where historical institutionalism has greatly influenced their educational systems. To begin with, the German vocational education and training (VET) system serves as an excellent illustration of historical institutionalism in action. Based on the nation's industrial background, the dual apprenticeship system integrates practical experience with educational courses. This system has developed over time, shaped by historical influences and the necessity to respond to globalization challenges (Thelen, 2004). Secondly, the educational system in the UK has been influenced by its extensive history of reforms and policies in education. Historical institutionalism aids in understanding the enduring nature of specific educational frameworks, like the separation between grammar schools and comprehensive schools, which are grounded in the nation’s social and political past (Green, 1990). Third, Japan's educational structure demonstrates its historical focus on centralized authority and consistency, originating from the Meiji Restoration. The government's involvement in education has been crucial in creating a system that prioritizes strict academic standards and a unified national curriculum (Schoppa, 1991). Ultimately, in Ghana, historical institutionalism has been applied to examine shifts in educational policy. The educational reforms in the country have been shaped by its colonial past and the political dynamics following independence, which have influenced the formulation and execution of educational policies (Foster, 1965).

3. Research Hypotheses

Understanding the impact of artificial intelligence on the development of education in future human societies is likely to be influenced by people's understanding of the capabilities and potential applications of artificial intelligence. This study examines how different levels of understanding—from limited to advanced—may influence these perceptions. A limited understanding of the role of AI in educational advancements can increase the risk of false or incomplete perceptions and potentially lead to fear or overly optimistic expectations in society. Concerns such as job displacement and the dehumanization of learning experiences may hinder the progress of this innovation and cause resistance to the integration of artificial intelligence in education due to fears of negative effects on educational quality and human interaction. Additionally, people may deny the capabilities of AI outright, leading to a gap in readiness to accept this innovation (Meikle & Bonner, 2024). This can make the innovation ineffective or less effective. Therefore, the developers of this innovation, with the help of regulatory and executive institutions, should ensure that society has a correct understanding and full knowledge of how to apply it in the educational system of each country, and adjust the new educational system accordingly.

The variable of understanding AI and how it is used to produce products and services is a reasonable function of an individual's previous level of education. It can usually be concluded that people with a higher level of education give more accurate answers. In the IPSOS survey, South Africans were the most likely to agree (78%) and the Japanese the least likely (41%) to have a good understanding of how AI is used to produce products and services. A survey found that about half of South Africans claim to know what AI is. However, there is a difference in the level of trust they have in AI, with 44% confirming frequent use, particularly through digital assistants such as Google Assistant and Siri (Jones, 2022). Another study by (Smith, 2023) of South African university students found that they use AI tools to enhance their academic understanding and performance. Students demonstrated a critical and nuanced understanding of AI-based tools, using them for tasks such as improving writing style, clarifying academic concepts, and structuring essays. South Africa has emerged as a leader in the development of AI in Africa, as evidenced by the significant increase in AI-related publications over the past decade. This reflects the growing expertise and understanding of AI among South African researchers and practitioners (Brown, 2023).

Nakada, et al. (2021) examined the cultural and ethical perspectives on AI and robots in Japan. It highlights that Japanese people often have a more emotional and less technical understanding of AI, influenced by cultural narratives and popular media. (Persson et al. 2021) compared attitudes towards AI in Japan and Sweden, finding that Japanese respondents generally have lower levels of familiarity with AI and higher levels of concern about its implications, such as job displacement. Brown's report showed that less than half of Japanese respondents claimed to have a good understanding of AI, and there was a low level of trust in companies that use AI, indicating a gap in knowledge and confidence in AI technologies (Brown, 2024).

These beliefs can influence the adoption of AI in education in several ways. First, given that only 35% of people believe that AI will impact their family's educational development in the next 3-5 years, there is no clear expectation or openness to integrating AI technologies into educational settings. This prediction could increase the demand for AI-based educational tools and platforms and encourage schools and educational institutions to use these technologies to meet the expectations of students and parents. Second, the fact that 64% of people already have a good understanding of AI products and services indicates a readiness to embrace AI innovations in other areas, such as teaching and learning. This familiarity can reduce resistance to new technologies and make it easier for educators and policymakers to implement AI-based solutions. As more people better understand and trust AI over time, they are likely to advocate for its use in education and accelerate its adoption. Overall, these beliefs indicate a positive environment for the growth of AI in education, where both demand and adoption are likely to support the integration of AI technologies to enhance learning experiences..

H1: Perceived AI understanding will positively influence the educational development and learning in next 3-5 years.

Countries with a higher number of educational institutions and older years of independence often might more advanced in using artificial intelligence than newly independent countries (Smith, 2023). The reason might be due to these countries have had more time to develop and reform their education systems that allow for the integration of advanced technologies and curricula that include AI education. The extensive network of educational institutions provides a strong infrastructure for knowledge dissemination and fostering innovation. Furthermore, the historical stability associated with older years of independence is often associated with sustained investments in education and technology, creating an environment conducive to advanced learning and research. This long-term commitment to education and technological advancement will enable these countries to cultivate a population that is proficient in artificial intelligence and will generate awareness and expertise in this field.

***H2**:* Countries with a higher number of educational institutions and an older record of independence year are likely to have a better understanding of AI due to their established educational infrastructure.

Countries with a higher understanding of AI and a longer history of independence are more likely to see a greater impact on the use of AI in educational advancements due to their strong educational infrastructure. This correlation can be attributed to the fact that countries with a longer history of independence have had more time to develop and invest in their education systems. Furthermore, a higher understanding of AI often indicates a country's commitment to technological advancement and innovation, which usually includes significant investments in education and research facilities. As a result, these countries are better equipped to build and maintain strong educational infrastructures, creating an environment where both traditional and modern educational needs are effectively met.

***H3**:* Countries with a higher AI understanding and an older independence year are likely to have a higher number of educational infrastructures.

4. Methodology

4.1. The variables

In this study, we developed nine key variables to understand the impact of AI on educational development across different countries. Amonge these variables include the country's name and continent, which provide geographical location. The country's independence year is considered to understand historical influences on its educational system. AI understanding refers to the level of knowledge and integration of AI technologies within the country. Education development influenced by AI measures how AI has contributed to advancements in the educational sector. The variance of AI understanding captures the risk in AI knowledge across various regions within the country, while the variance of educational development assesses the risk in educational progress influenced by AI. Finally, the number of educational institutions provides a quantitative measure of the country's educational infrastructure. Together, these variables offer a typical framework to analyze the interplay between historical context, AI integration, and educational development. Table 1 defines all variables and the type of variables in term of quantitative or qualitative in this study.

[Insert **Table 1** Here]

Except for countries and continent which data type is factor, the data type for all other variables are integer. There are two variables that we used natural logarithm to precise measure: AI understanding and AI influence of educational development and learning. Adopting a natural logarithm for variables in meta-analysis offers several advantages. Firstly, it helps to normalize the data, reducing skewness and making the distribution more symmetrical, which is crucial for accurate statistical analysis. This transformation also stabilizes the variance, making the relationships between variables more linear and easier to interpret. Additionally, using the natural logarithm can mitigate the impact of outliers, ensuring that extreme values do not disproportionately influence the results. By transforming these variables, we can achieve more reliable and meaningful comparisons across different studies, enhancing the robustness and validity of the meta-analysis findings.

4.2 Data

This study used IPSOS survey (2022) as one of raw data for developing further investigations to gain a deeper understanding of AI-understanding and educational development and learning. On page 5 of the report, a table reflects 28 countries using agreed opinion percentages for eight survey questions. Between November 19 and December 3, 2021, 19,504 adults aged 18-74 were interviewed in North and South America, Europe, Asia, Africa, and Oceania. Ipsos provides research and consulting services across. In the sample, approximately 1,000 individuals from Australia, Brazil, Canada, China (mainland), France, Germany, Great Britain, Italy, Japan, Spain, and the United States are included, while 500 individuals from Argentina, Belgium, Chile, Colombia, Hungary, India, Malaysia, Mexico, the Netherlands, Peru, Poland, Russia, Saudi Arabia, South Africa, South Korea, Sweden, and Turkey are included. According to the Global Advisor online platform, 28 countries were considered observations and the survey questions were considered variables.

[Inset **Table 2** Here]

The variable LN_Var_Ed is the natural logarithm (LN) of the variable Ed_Learn_Dev. Also, LN_Var_Und is the LN of the variable AI_Unders. We first take the variance of the variables and then take their LN. Logarithmic transformation helps normalize skewed data, making distributions more symmetric and closer to normality. This is especially important when variables exhibit exponential growth or have a wide range of values. Many nonlinear relationships between variables can be made linear by applying a log transformation. This simplifies model estimation and interpretation. Also, logarithmic transformation allows interpretation of coefficients as elasticities or percentage changes, which are often more meaningful for numeric variables.

The survey asked the interviewees to choose which of the 13 different life issues would most significantly change for them and their families in the next 3-5 years due to the increased use of AI. One of the questions was, “I have a good understanding of what artificial intelligence is.” Another question asked, “Among these, which do you expect to change most for you and your family in the next 3 to 5 years because of the increased use of AI?” Education or learning new things was one out of fourteen options. We looked through a variety of sources and discovered data about the number of educational institutions in each nation as well as the year of independence. The information in this study has a high degree of dependability, hence the findings are legitimate.

4.3 Analysis Methods

The study conducted meta-analysis to examine the relationship between educational development, learning outcomes, and people's understanding of AI in a country is a reasonable approach for the following reasons. Meta-analysis allows researchers to combine results from different countries, providing a more comprehensive and robust understanding of the relationship between the variables. This enhances the generalizability of the findings across different contexts and populations. Second, by pooling data from various countries, meta-analysis increases the sample size, which enhances statistical power and the ability to detect significant effects. This is particularly useful when individual countries have small sample sizes. Meta-analysis helps identify and account for variability among countries, such as differences in methodologies, sample characteristics, and measurement tools. This allows for a more nuanced understanding of how educational development and AI understanding interact across different countries. Meta-analysis can reveal overarching trends and patterns that may not be apparent in individual countries. This can provide valuable insights into the broader relationship between education and AI comprehension, helping to inform policy and practice. By synthesizing data from multiple sources, meta-analysis can improve the accuracy and reliability of the conclusions drawn. This is particularly important for making informed decisions about educational interventions and AI integration. Overall, a meta-analysis provides a rigorous and systematic method for examining the complex relationship between educational development, learning, and AI understanding, leading to more informed and evidence-based conclusions.

Data of the study is aggregated and with Meta-analysis as aggregated estimates of the relationship strength between two variables measured concurrently or without experimental manipulation. The results from each study are standardized to a common scale using various outcome measures like odds ratio, relative risk, risk difference, correlation coefficient, and standardized mean difference. The term "effect size" is used generically to denote the chosen outcome measure for a meta-analysis, without implying causality between the variables. We begin with $i = 1, \ldots, k$ independent effect size estimates, each estimating a corresponding true effect size. We assume that $y_i = \theta_i + e_i$, *where* y_i represents the observed effect in the country, θ_i *is the corresponding unknown true effect, and* e_i is the sampling error, with $e_i \sim N(0, v_i)$. Thus, the y_i *values are considered unbiased and normally distributed estimates of their true effects. The sampling variances (*v_i values) are assumed to be known. Depending on the outcome measure used, it may be necessary to apply bias correction, normalization, and/or variance stabilizing transformations to ensure these assumptions hold approximately true (Viechtbauer, 2010, 2014).

Common Effect Model assumes that all included countries estimate the same underlying effect. It is useful when the countries are believed to be very similar in terms of their populations, interventions, and outcomes. The common effect model provides a single pooled estimate of the effect size, assuming no variability between countries. Random Effects Model, unlike the common effect model, the random effects model accounts for variability between countries. This model is more appropriate when there are differences in country populations, methodologies, or other factors. It provides a more conservative estimate by incorporating between-country variability into the overall effect size. Prediction Interval provides an estimate of the range within which the effect size of a future study might fall. It is particularly useful for understanding the potential variability in effect sizes that might be observed in new studies.

5. Results

5.1 Descriptive statistics

Table 3 summaries statistical values for the variable.

[Insert **Table 3** Here]

According to table 3, the descriptive statistics outline key variables relating to education and AI in the dataset. The "Ed_Learn_Dev" variable reflects educational learning development with a mean of 36 and variability as indicated by a standard deviation of 10.38. The "AI_Unders" variable, measuring AI-related understanding, shows a mean of 64.25, suggesting a moderate level of AI knowledge, with some variability (SD = 9.77). The skewness and kurtosis values indicate data asymmetry and peakedness, highlighting variability in AI and education contexts. For instance, "LN_Var_Ed" (log-transformed variance in education) has a skewness of 1.57, implying a positive skew with occasional outliers. The table emphasizes disparities in education (e.g., "No_Ed_Ins" with high variance) and AI adoption. This data could inform targeted policies to bridge gaps in AI and education.

Figure 1 illustrates the growth of educational institutions in three regions—European, Asian, and other countries—over time, highlighting trends relative to their years of independence.

[Insert **Figure 1** Here]

In Europe, the number of educational institutions has steadily risen, with significant growth following the independence or consolidation of major countries. France leads with over 800 institutions established post-1789, reflecting its robust educational reforms during and after the French Revolution. Germany and Poland show notable growth, especially after their respective unification and independence periods (1871 for Germany and 1918 for Poland). Russia's institutions surged after 1990, coinciding with the post-Soviet era's push toward modernization. Great Britain, Spain, and Italy also show considerable educational expansion, reflecting their established histories in academia.

In Asia, India's educational growth post-1947 independence is remarkable, exceeding 4,000 institutions, indicating its commitment to education as a pillar for development. China's growth post-1912 aligns with its modernization efforts. Japan, South Korea, and Malaysia also show steady growth, with notable investments in education correlating with their economic transformations. Turkey and Saudi Arabia as middle east countries, despite earlier independence, display moderate growth compared to the larger nations, reflecting their evolving focus on education.

The United States, with independence in 1776, shows over 3,000 institutions, reflecting its historical emphasis on education as a driver for innovation and democracy. Latin American countries like Brazil, Mexico, and Argentina also experienced significant growth, with Brazil leading after its 1822 independence. Canada and Australia show moderate growth, aligning with their stable, developed economies. South Africa's growth post-1961 reflects a transition toward prioritizing education in the post-apartheid era. Overall, the figure demonstrates that independence often catalyzed educational development, with varying trajectories based on regional priorities, economic conditions, and societal needs.

5.2 Test of Hypothesis 1

The result for Multiple R is 0.8476 indicates a strong positive correlation between the dependent variable (AI*Unders) and the independent variable (Ed_Learn_Dev*). R^2 is 0.7184 means that approximately 71.84% of the variance in AI*Unders can be explained by Ed*Learn_Dev. Adjusted R^2 is 0.7075 adjusts the R^2 value for the number of predictors in the model, indicating a slightly lower but still strong explanatory power. Standard Error of Estimate is 5.2857 represents the average distance that the observed values fall from the regression line. F-statistic is 66.3168 with a p-value of 0 indicates that the model is statistically significant, meaning that Ed*Learn*Dev significantly predicts AI_Unders when ANOVA used. Intercept is 36.1448 with a standard error of 3.5929 and a t-value of 10.060 ($p = 0.0000$) suggests that when Ed*Learn*Dev is zero, the expected value of AI_Unders is 36.1448. The standardized coefficient (b*) of 0.848 fpr Ed_Learn_Dev indicates that for every one standard deviation increase in Ed*Learn*Dev, AI_Unders increases by 0.848 standard deviations. This coefficient is also statistically significant ($p = 0.0000$). Overall, the results suggest that educational learning development (Ed*Learn*Dev) is a strong and significant predictor of understanding AI (AI*Unders). The model explains a substantial portion of the variance in AI*Unders, and the relationship between the variables is both strong and statistically significant.

5.3 Test of Hypothesis 2

The statistical tests indicate that neither the Year nor the Number of Educational Institutions significantly predict AI Understanding, as shown by the high p-values ($p=0.6895$) in both the regression and ANOVA results. Additionally, the Shapiro-Wilk test ($W = 0.91745$, p-value = 0.03002) suggests that the residuals are not normally distributed, which may affect the reliability of these tests. The application of artificial intelligence (AI) in education is poised to significantly reduce the number of traditional educational institutions in the coming years. AI-driven platforms and tools offer personalized learning experiences, adaptive assessments, and on-demand tutoring, which can cater to individual student needs more efficiently than conventional classroom settings (Johnson, 2022). As these technologies become more advanced and accessible, there is a growing trend towards online and hybrid learning models that do not require physical infrastructure. This shift is likely to lead to a consolidation of educational institutions, with fewer but more technologically integrated schools and universities emerging to meet the changing demands of learners (Smith & Brown, 2023). Additionally, the cost-effectiveness and scalability of AI in education make it an attractive alternative for both students and educators, potentially accelerating the decline of traditional educational institutions (Williams, 2021).

5.4 Test of Hypothesis 3

Based on the multiple regression analysis, the model shows a very weak relationship (R-squared = 0.029) meaning neither No_Ed_Ins (p = 0.708) nor Year (p = 0.496) are statistically significant predictors of AI_Unders. The diagnostic plots show potential issues with the model assumptions. Based on the diagnostic tests for normality, Shapiro-Wilk test (p = 0.03) indicates residuals are not normally distributed and for Heteroscedasticity, Breusch-Pagan test (p = 0.42) suggests homoscedastic residuals. The diagnostic plots shows that non-linear patterns in residuals have potential outliers and deviation from normality in Q-Q plot.

[Inset **Figure 2** Here]

The understanding of AI products and services in a country is not necessarily influenced by its year of independence or the number of educational institutions it possesses. Instead, factors such as the quality of education, the presence of technology-driven curricula (Zhou, 2023), and the level of investment in AI research and development play more critical roles. Countries with newer independence or fewer institutions can still achieve high levels of AI literacy if they prioritize modern educational practices and foster environments that encourage technological innovation (Doe, 2022). Additionally, global access to online resources and international collaborations can bridge gaps in AI understanding, making it possible for any country to excel in AI regardless of its historical or institutional background (Smith & Lee, 2021). Therefore, the focus should be on enhancing the quality and relevance of education using AI and enhansing learners' ability to use AI to explore new educational experiences (Johnson, 2023).

5.5 Common and Equal Effect Model

The meta-analysis using a Common-Effects Model (CEM) with 28 countries ($k = 28$) reveals significant findings. CEM assumes that all countries estimate the same underlying effect. This means that the mutual impact of understanding AI and educational advances is true for all countries. For example, China (Chen, et al. 2012), India (Singh, et al, 2020), and Finland (Vainio, et al., 2021) are emphasizing the application of AI for lifelong educational learning. The total heterogeneity, represented by I^2=41.41% indicating moderate variability among the countries. The H^2=1.71 suggests that the total variability is 1.71 times the sampling variability. The test for heterogeneity, Q (df = 27) = 46.0850, with a *p-value* of 0.0125, shows significant heterogeneity among the countries. The model results indicate an estimate of 1.0033 with a standard error (*SE*) of 0.1899, yielding a *z-value* of 5.2820 and a highly significant *p-value* of less than 0.0001. The confidence interval (*ci*) ranges from 0.6310 to 1.3755, further supporting the robustness of the findings. These results underscore the consistency and reliability of the effect size across the included countries.

For policymakers, this highlights the importance of adopting a nuanced approach when designing and implementing educational policies. Tailored interventions that account for national differences in infrastructure, socio-economic conditions, and resource availability are essential to maximize the effectiveness of initiatives. Governments are encouraged to prioritize cross-national collaboration and share best practices, leveraging the strong underlying effect while addressing localized challenges.

These findings serve as a foundation for evidence-based policies aimed at fostering equitable and impactful progress.

5.6. Fixed Effect Model

The meta-analysis using a Fixed-Effects with Moderators Model with 28 countries (k = 28) reveals several key findings. The residual heterogeneity, represented by $I^2 = 43.57\%$, indicating a moderate level of unaccounted variability among the countries. The $H^2 = 1.77$ suggests that the unaccounted variability is 1.77 times the sampling variability. Notably, the R^2 value is 0.00%, indicating that the moderators did not account for any of the heterogeneity. The test for residual heterogeneity, QE (df = 26) = 46.0725, with a p-value of 0.0090, shows significant residual heterogeneity. The test of moderators, QM (df = 1) = 0.0125, with a p-value of 0.9108, indicates that the moderators did not significantly explain the variability in the effect sizes. These results highlight the presence of unexplained heterogeneity and suggest that the included moderators did not contribute to accounting for this variability.

The figure 2 summarizing countries using risk ratios (RR) and confidence intervals (CI). A meta-analysis the figure summarizing countries using risk ratios (RR) and confidence intervals (CI) provides a comprehensive overview of the combined results from multiple countries.

[Inset **Figure 3** Here]

Events refers to the observed occurrences of the outcome of interest in each group within the countries. It provides the raw data used to calculate the risk ratios. *Risk Ratios* (RR) quantifies the risk of an outcome in one group compared to another. An RR greater than 1 suggests a higher risk in the experimental group compared to the control group, while an RR less than 1 suggests a lower risk. The confidence interval 95% indicates the uncertainty around the RR estimate. If the CI crosses 1, it implies that the result may not be statistically significant, meaning the true effect could be no different from no effect. The *weights* assigned to each study reflect their contribution to the overall result. In the common effect model, larger countries with more precise estimates typically receive more weight. In the random effects model, the weights also consider the variability between countries, often resulting in more balanced contributions from smaller countries.

In term of Heterogeneity, $I^2 = 54.57\%$ in which indicates moderate heterogeneity among the included countries. It means that about 54.6% of the variability in the study results is due to differences between the countries rather than random chance. Moderate heterogeneity suggests that while the countries are not completely homogeneous, they are not entirely dissimilar either. $\tau^2 = 0.0087$ represents the variance of the effect sizes in the random effects model. A higher τ^2 value indicates greater variability between the countries. $p = 0.0003$ suggests significant heterogeneity among the included countries. A low p-value (typically < 0.05) indicates that the observed variability is unlikely to be due to random chance alone.

Pooled Risk Ratios have two effects. First one is common-effect with RR = 1.12 [1.09, 1.16]. This suggests a 12% increase in risk in the experimental group compared to the control group, with a narrow and statistically significant confidence interval. Second is random effects. The pooled RR might be slightly different due to the inclusion of between-study variability. Overall, the meta-analysis indicates a slight increase in risk, as evidenced by the pooled RR values greater than 1, with narrow and significant confidence intervals. This suggests that the effect observed is consistent and unlikely to be due to random chance.

The figure 4 shows a funnel plot showing the relationship between the standard error and the development of educational learning in different countries. Countries such as Japan, Germany, and France are at the bottom, with smaller standard errors, reflecting more precise estimates. On the other hand, countries such as Peru, South Africa, and Argentina are at the top, indicating higher standard errors and less precise estimates. The dashed vertical line represents the overall pooled estimate. Symmetry around this line indicates no diffusion bias, while asymmetry (if present) may indicate heterogeneity or bias. Expanding countries emphasize global diversity in educational learning development practices. European countries along with developed countries are on the left side of the red line and developing countries are on the right side.

[Insert Figure 4 here]

6. Conclusion

Using meta-analysis, this study integrates constructs based on a survey and provides insights into the main factors affecting the adoption and use of AI technology in education across 28 countries. To determine the investment strategy in educational structures in the coming years, the model examines the relationship between the mutual relationship between the understanding of artificial intelligence and educational learning and the number of educational institutions for the countries studied. Studies show that the characteristics of countries that became independent earlier than other countries and have more educational institutions should be receptive to artificial intelligence innovation. These countries show a very close connection between education and understanding of AI technology. This means that knowledge about educational environments is one of the most important variables for the development of educational environments. Therefore, training and participation of people to use these technologies is important and should be carefully planned according to the characteristics of the countries. Direct measures to educate people about artificial intelligence should be developed, but the traditional development of the physical number of educational institutions has no effect on this issue. However, there were enough differences to show that local contexts in different countries need to be taken into account as we face the critical issue of sustainability and achieving the Sustainable Development Goals through AI technology. Our model provides a basis for future research and practical solutions for the adoption and use of sustainable technologies.

The findings from the analysis underscore the substantial impact of artificial intelligence (AI) on education, revealing a strong and statistically significant relationship between AI-related understanding and key variables. The model explains a significant portion of the variance in AI understanding, highlighting the transformative role AI can play in modern education systems. These results not only validate the growing importance of AI but also signal the need for strategic adjustments in how education is structured and delivered globally for sustainable society.

As AI becomes increasingly integrated into education, its scalability and cost-effectiveness position it as a powerful tool for both learners and educators. Williams (2021) points out that AI's ability to streamline resources and customize learning experiences could accelerate the decline of traditional educational institutions, paving the way for more technologically advanced and efficient alternatives. Smith and Brown (2023) argue that this shift is likely to result in the consolidation of educational institutions, with fewer but more technologically integrated schools and universities emerging to meet the evolving demands of students. This trend highlights the pressing need for education systems to adapt by focusing on technological integration rather than adhering to outdated models of expansion or historical timelines.

Given these dynamics, the emphasis should shift to increasing the effectiveness of educational communication by emphasizing AI-enabled educational tools. Policymakers should recognize that rapid advances in AI require an education system that is not only adaptive, but also forward-looking and grounded in each country's educational environments. Prioritizing communication ensures that students are equipped with the skills and knowledge necessary to thrive in an AI-enabled world. This approach requires moving away from traditional measures of educational success, and focusing on fostering meaningful, technology-enabled learning experiences.

Furthermore, international cooperation is essential to address the diversity in how countries adopt and implement AI in education. Governments are encouraged to share best practices, learn from each other, and develop policies that take into account local challenges while leveraging the strong underlying impact of AI integration. This shared approach can help reduce disparities between countries and ensure long-term sustainability, and ensure that the benefits of AI in education are equitably distributed globally. By strengthening partnerships and pooling resources, countries can create an inclusive education landscape that maximizes the potential of AI.

As a result, the integration of AI into education presents both a challenge and an opportunity for policymakers and educators not only at the local level but also at the international level. While the decline of traditional educational institutions and systems may seem disruptive, there is an opportunity to reimagine education as more accessible, efficient, and relevant to the needs of a rapidly changing world. These findings provide a strong foundation for evidence-based policies aimed at fostering equitable progress globally, and enable governments to make this transformation with confidence. By prioritizing quality, relevance, and collaboration, stakeholders can ensure that education evolves in ways that are impactful and inclusive, meeting the demands of learners in the age of AI. This emphasizes the need for governments and institutions responsible for educational development to work together with other countries, regardless of their historical, geographical, or cultural location.

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Table 1. Variables of the study

Var. No	Variables Symbol	Definition	Type
1	*Trail*	An interchange for the sequence number of countries in Meta-Analysis	Integer
2	*Countries*	Name of countries in this study	Factor
3	*Continent*	Name of continent where the country is located in	Factor
4	*Indep_Year*	The year that the country officially declared its independency	Integer
5	*Ed_Learn_Dev*	IPSOS survey results of the influence of AI in Education	Integer
6	*LN_Var_Ed*	Natural Logarithm of Variance of *Ed_Learn_Dev*	
7	*AI_Unders*	A good understanding of the AI products and services	Integer
8	*LN_Var_Und*	Natural logarithm of Variance of *AI_Unders*	Integer
9	*No_Ed_Ins*	The number Educational Institution of a countries	Integer

Table 2. Dataset of the study

Trail	*Coun_tries*	*Cont_inent*	*Indep_Year*	*Ed_Learn _Dev*	*LN_Var_Ed*	*AI_ Unders*	*LN_Var_ Und*	*No_Ed_ Ins*
1	Argentina	South A	1816	47	5.33	66	0.15	146
2	Australia	Oceania	1901	30	0.93	59	0.93	187
3	Belgium	Europe	1830	26	3.00	60	0.59	142
4	Brazil	South A	1822	41	1.33	69	0.93	1264
5	Canada	North A.	1867	32	0.33	59	0.93	383
6	Chile	South A	1810	44	3.00	76	5.33	130
7	China	Asia	1912	43	2.37	67	0.33	2495
8	Colombia	South A	1810	46	4.48	71	1.81	299
9	France	Europe	1789	15	14.81	50	7.26	625
10	Germany	Europe	1871	19	9.48	50	7.26	461
11	Great Britain	Europe	1707	24	4.48	57	1.81	337
12	Hungary	Europe	1848	33	0.15	67	0.33	69
13	India	Asia	1947	42	1.81	72	2.37	5349
14	Italy	Europe	1861	25	3.70	42	17.93	289
15	Japan	Asia	1947	15	14.81	41	19.59	992
16	Malaysia	Asia	1957	41	1.33	61	0.33	351
17	Mexico	South A	1821	47	5.33	74	3.70	1139
18	Netherlands	Europe	1648	27	2.37	65	0.04	129
19	Peru	South A	1821	52	10.70	76	5.33	125
20	Poland	Europe	1918	32	0.33	66	0.15	408
21	Russia	Europe	1990	36	0.04	75	4.48	1010
22	Saudi Arabia	Asia	1932	41	1.33	73	3.00	68
23	South Africa	Africa	1961	50	8.33	78	7.26	124
24	South Korea	Asia	1945	40	0.93	72	2.37	401
25	Spain	Europe	1808	36	0.04	62	0.15	276
26	Sweden	Europe	1523	30	0.93	60	0.59	46
27	Turkey	Asia	1923	45	3.70	68	0.59	209
28	US	North A.	1776	27	2.37	63	0.04	3180

Table 3. Descriptive Statistics of the numeric variables

	Valid N	Mean	Median	Min	Max	Variance	Std.Dev.	Skewness	Kurtosis
Indep_Year	28	1849	1855	1523	1990	10425.951	102.108	-1.358	2.769
Ed_Learn_Dev	28	35.21	36.00	15.00	52.00	107.73	10.38	- 0.35	- 0.77
LN_Var_Ed	28	3.85	2.37	0.04	14.81	17.36	4.17	1.57	1.83
AI_Unders	28	64.25	66.00	41.00	78.00	95.53	9.77	- 0.86	0.37
LN_Var_Und	28	3.41	1.37	0.04	19.59	24.39	4.94	2.35	5.56
No_Ed_Ins	28	736.93	318.00	46.00	5,349.00	1,348,213.48	1,161.13	2.94	9.35

Figure 1. Number of Educational Institutions and Year of Independent

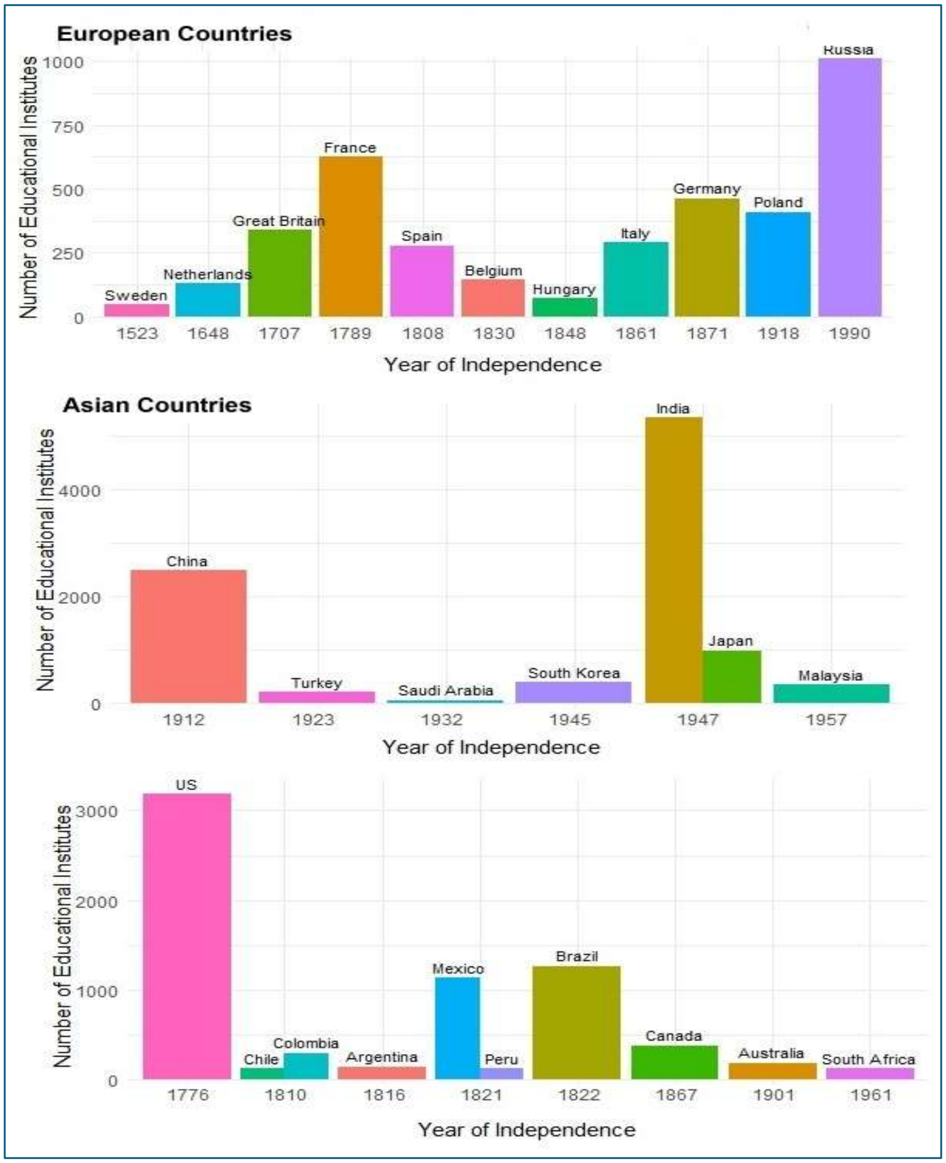

Figure 2. Residuals vs Fitted and Q-Q Plot

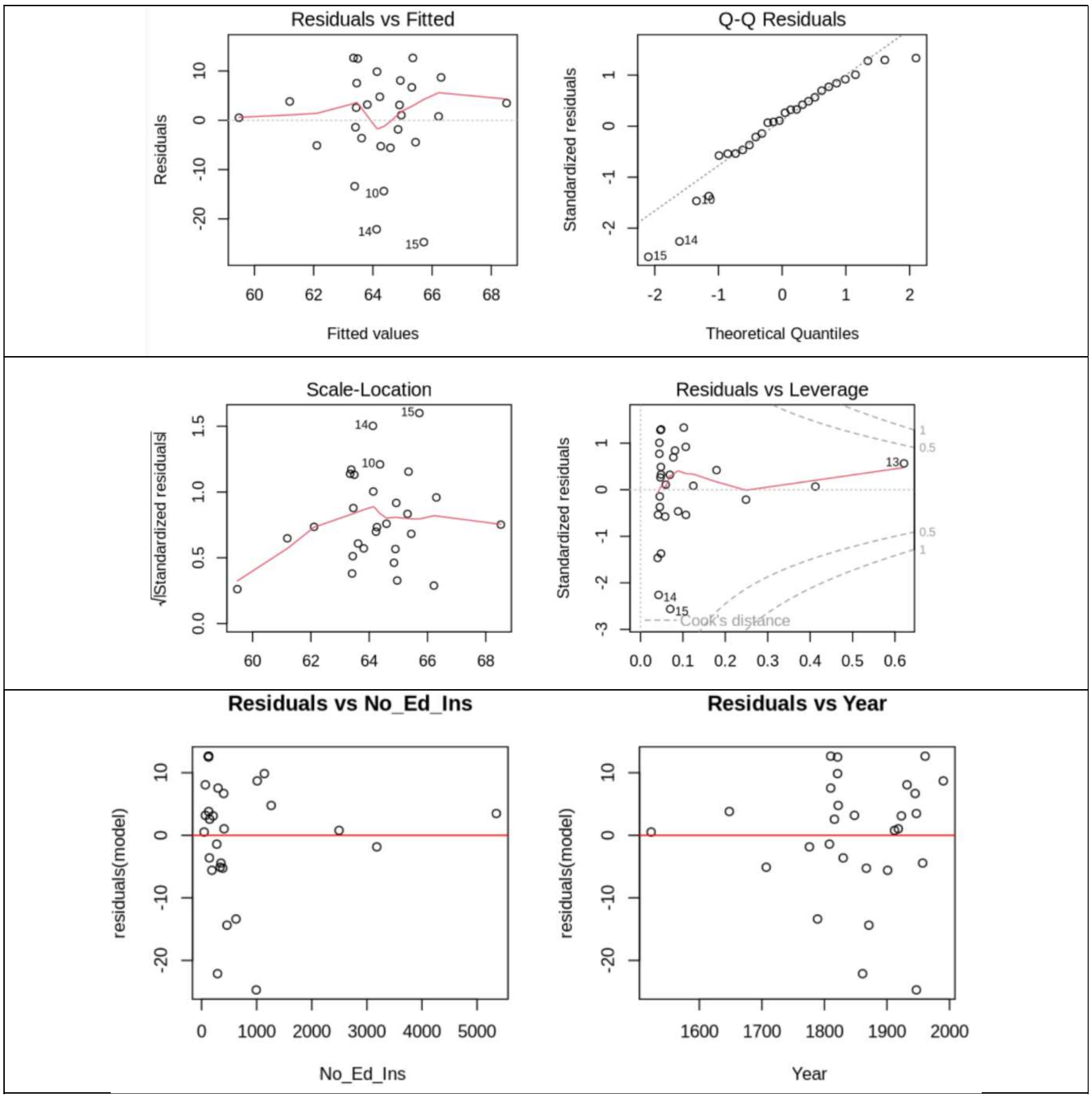

Figure 3 Common and Random Effects Model using Forest Plot

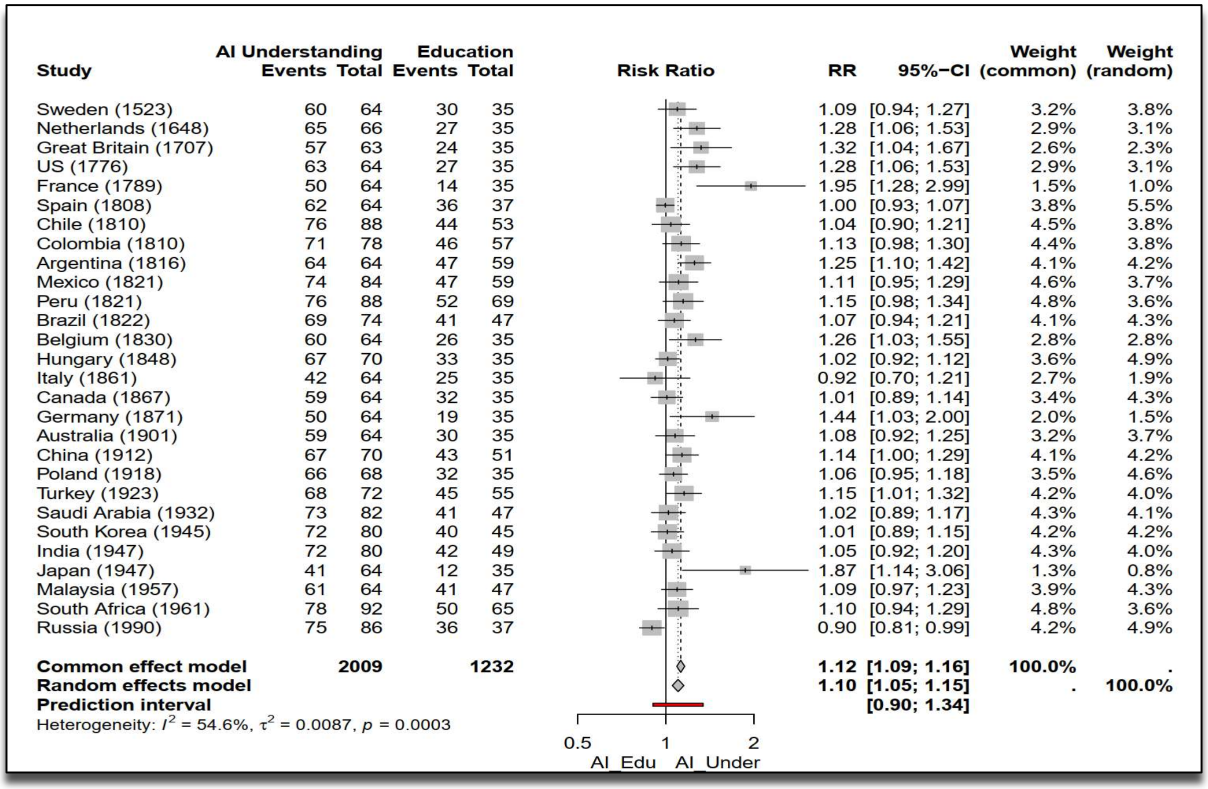

Figure 4. Funnel plot of the countries