Malta Journal of Education, Volume 6, No 1, 22-43
Minds and Machines Unite
https://doi.org/10.62695/TQQM2623

AI Adoption Among Europe's School Evaluators: Awareness and Challenges

Keith Aquilina
Ministry for Education and Employment
https://orcid.org/0009-0007-0705-4078

Abstract

This study examines European external school evaluators' awareness, perceptions, and acceptance of artificial intelligence (AI) in external school evaluation. Drawing on the Technology Acceptance Model (TAM) theoretical framework, this research explores how evaluators' familiarity with AI, perceived ease of use (PEoU), and perceived usefulness (PU) shape their willingness to integrate AI tools. A mixed-methods approach incorporated a questionnaire (n=56) and semi-structured interviews (n=6), revealing moderate awareness of AI's capabilities and an overall optimism about potential efficiency gains. However, adoption remains limited, hindered by insufficient training, infrastructural challenges, and ethical concerns regarding data privacy and algorithmic bias. The findings underscore the importance of targeted professional development, robust ethical frameworks, and adequate technological support for successful AI adoption in external school evaluation processes. By addressing these barriers, policymakers and inspectorates can leverage AI's potential to enhance the accuracy, consistency, and efficacy of external school evaluations.

Keywords

Artificial Intelligence (AI), Technology Acceptance Model (TAM), External School Evaluation, Evaluator Awareness, Educational Inspectors, Mixed-Methods Research, Ethical Considerations, School Improvement

Introduction

The global introduction of ChatGPT by OpenAI in 2022 sparked widespread interest in AI applications across various sectors, including education. AI in Education (AIED) is not a novel concept; its roots stretch back to the 1950s when the first AI program was developed to teach a computer to play checkers. Since then, AIED has focused on developing AI-powered technologies to enhance teaching and learning experiences. Over the past 60 years, AI has evolved from simple applications to sophisticated tools capable of personalising learning environments, grading assignments, and supporting administrative tasks (Lynch, 2023; Guan et al., 2020).

Contact: Keith Aquilina, keith.aquilina@ilearn.edu.mt

Today, AI is gaining mainstream attention, propelled by rapid advancements in technology and the enactment of various policies and regulations, like the Artificial Intelligence Act (European Commission, 2025). While AI applications in teaching and learning have garnered increased focus, their adoption in external school evaluation processes remains under-researched. External evaluations are crucial for maintaining standards and promoting school improvement through data-driven assessments. Understanding how external evaluators perceive and accept AI tools is essential for enhancing these evaluation processes and educational outcomes.

This study aims to fill this gap by investigating European school evaluators' awareness and adoption of AI, using the Technology Acceptance Model (TAM) as a theoretical framework. The research addresses the following questions: (1) To what extent are European evaluators aware of AI's capabilities and potential applications in school evaluation? (2) How do European evaluators perceive the ease of use and usefulness of AI-powered tools?

This research contributes to a deeper understanding of the potential integration of AI in external school evaluations by understanding how evaluators approach AI, their level of awareness, and the factors influencing adoption. As education systems worldwide increasingly rely on data-driven assessments to promote school improvement, insights from this study can inform policymakers, inspectorates, and technology developers.

The paper first explores the evolving role of external school evaluators and how European inspectorates are integrating technology into their evaluation processes. It then discusses the relevance of the TAM model in understanding AI integration in educational evaluation. After reviewing relevant literature, the study's methodology is detailed, and the findings are presented. Based on the literature and the TAM, findings indicate key factors impacting AI adoption.

Literature Review

AI in Education and External School Evaluation

While AI has been increasingly adopted in various industries, including education, its application in external school evaluations is still emerging, with limited empirical research addressing this area (Holmes et al., 2019). This nascent stage is due to the recent focus on AI within educational contexts, driven by advancements in machine learning, data analytics, and natural language processing.

Current literature on AIED primarily focuses on its applications in teaching, learning, and administrative processes. AI technologies such as adaptive learning systems, automated grading, and administrative data management have been explored extensively, with studies demonstrating their potential to enhance educational outcomes and efficiency (Guan et al., 2020; Sprenger & Schwaninger, 2021). In recent developments, the Dutch Data Protection Authority has published advice regarding the supervision of AIED, emphasising the need for ethical considerations and regulatory frameworks to manage the deployment of AI technologies in educational settings (DataGuidance, 2023). OECD (2023) emphasises the effective and equitable use of AIED, providing essential guidelines and guardrails for stakeholders in the educational sector. This report highlights the opportunities and challenges presented by AI technologies, particularly in shaping digital education ecosystems across OECD countries. Additionally, through the Artificial Intelligence Act (European Commission, 2025), the European Parliament has recognised the potential of AIED while also addressing the risks associated with bias and discrimination. It calls for a careful approach to AI deployment, ensuring that it respects fundamental rights and promotes equity in educational access.

The role of inspectorates in holding schools accountable and promoting their improvement constantly evolves, and the boundary between inspecting and advising or supporting is increasingly blurred (OECD, 2013). Recent studies into school inspection across Europe reveal that even though inspectorates hope for the same outcomes, they adopt very different approaches to governing education (Ehren & Baxter, 2021; OECD, 2015). These range from systems that focus on regulation and compliance, such as Sweden, to those that take a more developmental approach, such as Scotland, which largely relies on school self-evaluation to monitor progress (MacBeath, 2019; SICI, n.d.). Countries such as Germany, Estonia, and Sweden have unique approaches to school inspections, with varying emphases on teacher observation, evidence, compliance, and communication with parents. (Greatbatch & Tate, 2019; Baxter & Ehren, 2014). In the UK and elsewhere, evaluators are tasked with observing teaching, assessing learning outcomes, discussing issues with school staff, and preparing reports on teaching quality, student development, and resource management. They also ensure statutory educational requirements are met, verify the maintenance of school facilities, and oversee the provision of medical and meal services (Department for Education, 2023). The role of school evaluators in Europe is influenced by political, historical, social, and economic factors, and there is ongoing research into how inspection promotes good education and student achievement in schools (Baxter & Ehren, 2014; SICI, n.d.). The varying approaches of inspectorates are mirrored in the integration of technology for evaluation processes.

The use of technology in educational evaluations is evolving, particularly in the digitisation of inspection processes. Specific European inspectorates, such as Ofsted, the official body for inspecting schools in England, have begun using digital tools to streamline administrative tasks and enhance data collection during inspections (Harford, 2018). School evaluators are increasingly using technology as part of their inspection process. They often interact with various technological tools and systems for data collection and analysis, reporting, and communication as part of their responsibilities. For instance, in the past years, Ofsted has transitioned to digital tools, with evaluators using digital devices instead of pen and paper during school inspections (Harford, 2018). Ofsted acknowledges the integral role of digital technology in modern educational settings, encouraging its use for various purposes, such as recording observations and tracking progress (Ofsted, 2024). This indicates a clear shift towards the integration of digital technology in the school inspection process for various purposes (Kooser, n.d.), including recording observations, gathering evidence digitally, taking notes, and analysing data.

Overall, integrating technology in the school inspection process significantly improves efficiency, accuracy, and productivity, benefitting both entities and evaluators alike (SafetyStratus, n.d.). The integration of technology modernises the inspection process, enabling evaluators to work more effectively and provide more comprehensive evaluations. (Martínez-Serrano et al., 2023). Integrating digital technology into school external quality assurance processes offers multiple benefits:

- Efficiency: Digital tools streamline evaluation procedures by automating data collection and analysis, reducing administrative burdens and saving time (Joint Research Centre, 2023; Selwyn, 2016).

- Personalisation: Technology enables evaluators to tailor feedback and assessment methods to each school's specific needs, enhancing the relevance and effectiveness of evaluations (Holmes et al., 2019).

- Data-driven insights: Advanced analytics provide evaluators with real-time data and trends, allowing for more informed decision-making and targeted interventions (Chen et al., 2020).

- Collaboration: Digital platforms facilitate communication among educators, administrators, and external evaluators, promoting transparency and shared understanding (Fullan & Langworthy, 2014).

- Continuous Improvement: Ongoing access to data and feedback loops supported by technology fosters a culture of continuous improvement, helping schools to adapt and enhance their practices over time (Bryk et al., 2015).

The benefits of employing digital technology in schools' external quality assurance support the argument for its integration to enhance educational outcomes (European Commission, 2020; EACEA(Eurydice), 2019).

Evaluators' level of digital competence and ability to analyse large volumes of data are very relevant to improving the educational system (Martínez-Serrano et al., 2023). Martínez-Serrano et al. (2023) highlight the necessity for educational evaluators to develop digital competence as part of their professional skills. This competence is essential for effectively collecting and analysing evidence during inspections and supporting school improvement efforts. The research underscores the importance of ongoing training in digital literacy for evaluators to enhance their inspection practices (Martínez-Serrano et al., 2023).

Inspectorates and educational bodies worldwide are exploring or implementing AI to enhance their inspection and evaluation processes. For instance, in England, there are plans for training school evaluators on AI applications to enhance decision-making, and they are using AI in risk assessments to determine whether 'good' schools require full inspections or shorter visits (Ofsted, 2023). This highlights AI's potential to automate processes and analyse large datasets, particularly text, to generate insights supporting inspections and regulatory activities while maintaining ethical standards (Ofsted, 2023).

Technological advancements by inspectorates demonstrate a growing recognition of the potential for digital tools to improve the efficiency and accuracy of school evaluations (Harford, 2018; Martínez-Serrano et al., 2023; UNESCO, 2019). However, these practices primarily involve existing digital technologies, with AI integration still in its early stages. The use of AI for more complex tasks, such as predictive analytics or automated report generation, has yet to be widely adopted or studied within these inspectorates. This gap presents an opportunity for research to explore how AI can build on these existing technologies to enhance further external school evaluations (OECD, 2023; Zawacki-Richter et al., 2019). As the OECD (2023) notes, integrating AI into educational evaluation requires careful consideration but holds significant promise for improving the effectiveness of evaluation processes.

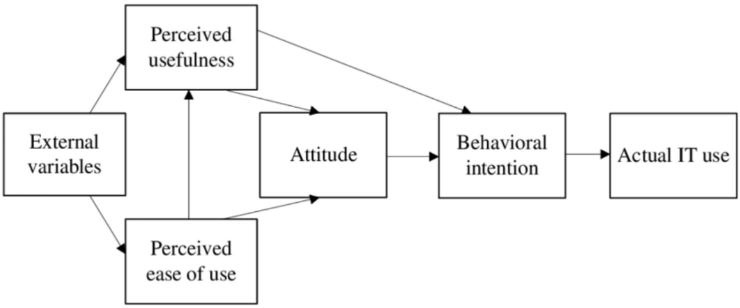
The Technology Acceptance Model

This study is grounded in the TAM theoretical framework, which is widely recognised in the field of technology adoption and use (Davis, 1989; Venkatesh & Bala, 2008). The TAM offers a robust framework for understanding the factors that influence the adoption of emergent technologies such as AI. TAM posits that Perceived Usefulness (PU) and Perceived Ease of Use (PEoU) are primary determinants of users' attitudes towards a technology, which in turn affect their behavioural intention to use it (Davis, 1989; Venkatesh & Bala, 2008). Behavioural intention is a key factor that leads people to actually use the technology (Alharbi & Drew, 2014). TAM is used to study the adoption of digital technologies in educational settings (Granić & Marangunić, 2019; Lin & Yu, 2023), to predict students' and educators' behavioural intention to use and actual use of digital technologies (Marikyan & Papagiannidis, 2024), and to identify areas for improvement and better understand the conditions for successful technology adoption (Granić, 2022; Al-Adwan et al., 2023).

The TAM comprises several variables explaining behavioural intentions and the use of technology directly or indirectly (i.e., PU, PEoU, attitudes toward technology). It has been extended by external variables, such as self-efficacy, subjective norms, and facilitating conditions of technology use (Schepers & Wetzels, 2007). The TAM has gained considerable prominence, mainly due to its transferability to various contexts and samples, its potential to explain variance in the intention to use or the use of technology, and its simplicity of specification (e.g. Marangunić & Granić, 2015).

Figure 1

Technology Acceptance Model (Davies, 1989)



While TAM has been widely applied to various educational contexts, its application to AI in school evaluations remains largely unexplored (Granić & Marangunić, 2019; Zawacki-Richter et al., 2019; Venkatesh & Davis, 2000). Most studies focus on mainstream educational technologies or internal school processes, leaving the external evaluation aspect underexplored (Scherer et al., 2019; Vate-U-Lan, 2020). The limited application of AI in school evaluations can be attributed to the general uncertainty surrounding AI's practical benefits and implications in this context (Holmes et al., 2019; Chen et al., 2020). Additionally, existing literature often overlooks the potential ethical concerns associated with AI adoption, such as data privacy and algorithmic bias, which are crucial for understanding evaluators' hesitancy or resistance to AI (Morley et al., 2020; Araujo et al., 2020; Selwyn, 2021). Given the nascent stage of AI in school evaluations, this study seeks to apply TAM to explore evaluators' attitudes, beliefs, and perceptions about the relevance of technology in their role. The model provides valuable insights into how well AI is accepted and utilised by evaluators and potential barriers to AI adoption. These factors are particularly relevant in school evaluations, where the stakes are high, and the accuracy of assessments is paramount (Alharbi & Drew, 2014).

There is a noticeable gap in applying TAM to study AI adoption in the context of external school evaluations. This study aims to fill this gap by leveraging TAM to investigate how school evaluators perceive AI-powered tools in external evaluations. By focusing on PU, PEoU, and awareness, the research seeks to identify the key factors influencing AI adoption among school evaluators.

In summary, existing research demonstrates a growing recognition of AI's potential in educational contexts, but external school evaluation remains underexplored. Building on the TAM, this study examines how AI readiness, perceived usefulness, and ease of use shape evaluator attitudes and intentions.

Methods

This study employed a mixed-methods approach, combining quantitative and qualitative methods to explore European school evaluators' awareness and adoption of AI in external school evaluations. Mixed-methods research is well-suited for studying emerging technologies where user perceptions are still developing and the practical applications are not yet fully realised (Sprenger & Schwaninger, 2021).

An online survey was distributed to European inspectorates, targeting members of the Standing International Conference of Inspectorates, which comprises national and regional inspectorates and organisations dedicated to the external evaluation of education. The survey, conducted between March and April 2024, received responses from 56 individuals, with countries with the highest representation being: Portugal (n=20), Malta (n=10), the United Kingdom (n=10), and Bulgaria (n=6). The survey included multiple-choice, Likert scale, and open-ended questions to assess participants' familiarity with AI, PU, and PEoU regarding AI tools in school evaluations (Vomberg & Klarmann, 2022).

Following the survey, respondents had the option to volunteer for an online interview. Six evaluators from Belgium, France, the United Kingdom, the Netherlands, and Malta were chosen at random, ensuring only that they are from different countries, and interviewed in July 2024. The semi-structured interviews aimed to gain deeper insights into the participants' experiences, perceptions, and challenges related to AI adoption in school evaluations. Each interview lasted approximately 45 minutes and was conducted online to accommodate geographical distances.

Survey data was analysed using descriptive statistics to summarise demographic information and key variables related to AI awareness, PU, and PEoU. The quantitative analysis provided an overview of the general trends and patterns among the participants. Qualitative data from open-ended survey responses and interview transcripts were analysed using thematic analysis (Braun & Clarke, 2006). The qualitative data was coded to identify themes and any connections that characterised them (Rogers, 2018). The process involved reading and re-reading the data to become immersed and familiar with its content, generating initial codes to identify significant features of the data relevant to the research questions, collating codes into potential themes and gathering all data relevant to each theme. This was followed by refining themes to ensure they accurately represented the data. This allowed the researcher to identify, analyse and interpret patterns of meanings within the qualitative dataset so as to draw meaningful conclusions (Terry et al., 2017).

MAXQDA software was used to organise and code the qualitative data. To ensure confidentiality, participants were assigned pseudonyms (Evaluator_1 to Evaluator_6).

Participants were informed about the study's purpose, procedures, and their rights, including the voluntary nature of participation and the assurance of confidentiality. Informed consent was obtained from all participants prior to data collection. Data was securely stored and anonymised to protect participants' identities.

The data-gathering tools were guided by the principles of transparency and accountability, ensuring that the questions were clear, unbiased, and relevant to the research objectives (Guthrie et al., 2013). The survey was pilot-tested with an evaluator to ensure the clarity and relevance of the questions. Combining quantitative and qualitative data allowed for cross-validation of findings. The survey also focused on user-friendliness, with clear instructions and a logical flow to encourage participation and honest responses (Vomberg & Klarmann, 2022). The rigorous and systematic process ensured that the data-gathering tools were valid and reliable.

Findings

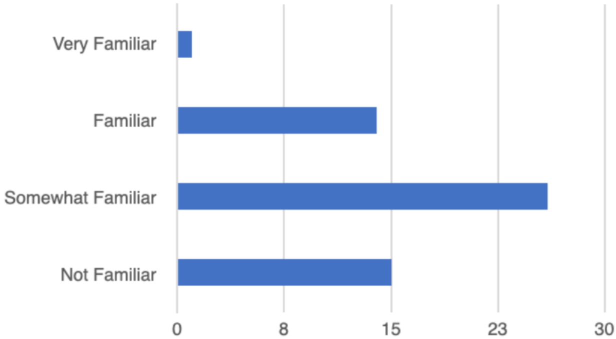
This section presents the findings of the study, integrating quantitative and qualitative data to address the research questions. The results are organised around key themes derived from the TAM and the research questions: awareness and familiarity with AI, perceived ease of use, perceived usefulness, barriers and ethical concerns. The most common role represented was that of an evaluator (including inspector and education officer; n=49), but there were other roles, primarily senior positions in inspectorates. Participants' experience in educational evaluation varied significantly, with an average of 14.7 years, a median of 13.1 years, and the most frequent experience level being 16 years. The varied experience levels across participants suggest a broad base of expertise in educational evaluation, which could influence the openness to and challenges of AI adoption.

Awareness and Familiarity with AI

The study explored the extent to which European school evaluators are aware of AI's capabilities and potential applications in school evaluation. Among the fifty-six survey participants, twenty-six reported being somewhat familiar with emerging technologies, including AI, machine learning, data analytics, and augmented reality. Fifteen participants indicated they were unfamiliar with these technologies, while the remaining 15 claimed varying degrees of familiarity. Moreover, in the survey's open-ended questions, 24 respondents indicated insufficient knowledge about the use of AI in external evaluations of schools.

Figure 2

Familiarity with Emerging Technologies



The interviews revealed significant variations in familiarity with AI among evaluators. Evaluators 5 and 6 demonstrated strong understanding and practical experience with AI tools. For instance, Evaluator_5 stated, "I am working on AI-related projects, particularly in data analysis and training simulations." Similarly, Evaluator_6 mentioned using AI tools to streamline report writing. In contrast, Evaluator_4 acknowledged awareness of AI's potential in education but expressed caution, noting, "AI can enhance adaptive testing and provide valuable insights, but we need to be cautious about ethical implications." Evaluators 1, 2, and 3 exhibited limited familiarity. Evaluator_1 admitted, "I know about AI only through mentions of tools like ChatGPT, but I have not engaged with it professionally."

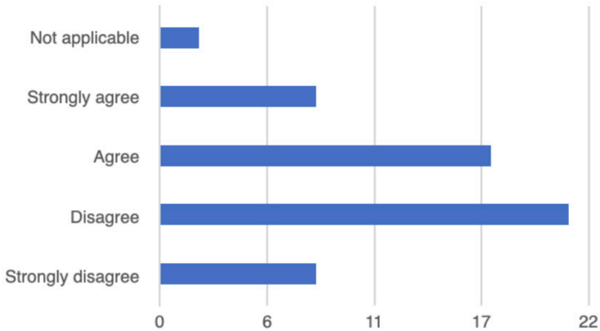
These findings indicate a moderate awareness of AI among school evaluators, with a significant portion unfamiliar or only somewhat familiar. Those with higher familiarity are more likely to have engaged with AI tools and recognise their potential applications in evaluation processes.

Perceived Ease of Use of AI Tools

This section examines how evaluators perceive the ease of use of AI-powered tools in school evaluations. When asked about their perceptions of the effort required to use AI tools, 25 participants agreed or strongly agreed that AI tools are easy to use. Twenty-nine believed that using AI tools would require significant effort.

Figure 3

Confident in Using AI for External School Evaluation Processes



Evaluators familiar with AI find it relatively easy to integrate it into their workflows. For example, Evaluator_6 acknowledged the ease of using specific AI tools but also emphasised the importance of training and the potential difficulty in ensuring accurate implementation. Those with low familiarity perceived AI as irrelevant to their work or potentially difficult to use. Evaluator_1, who claimed to have no experience with AI, did not see the need for its use in their current practices and expressed concerns about adopting new technologies without adequate understanding.

Perceived ease of use varies among evaluators, influenced mainly by their familiarity with AI. The need for comprehensive training emerges as a crucial factor in enhancing perceived ease of use.

Perceived Usefulness of AI in Evaluations

This section explores evaluators' perceptions of the usefulness of AI-powered tools in enhancing school evaluation processes.

Despite their limited familiarity, a majority of participants recognised AI's potential positive impact. Thirty-nine participants agreed that AI could improve the efficiency and accuracy of school evaluations. Ten participants were unsure about AI's usefulness, and seven participants disagreed that AI would be beneficial.

Figure 4

AI Can Enhance the Efficiency and Accuracy of External School Evaluation Processes

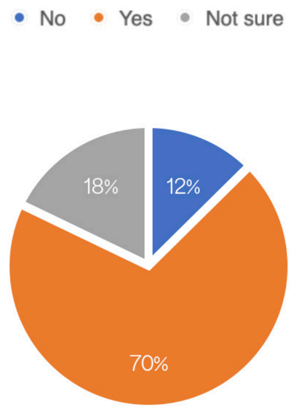
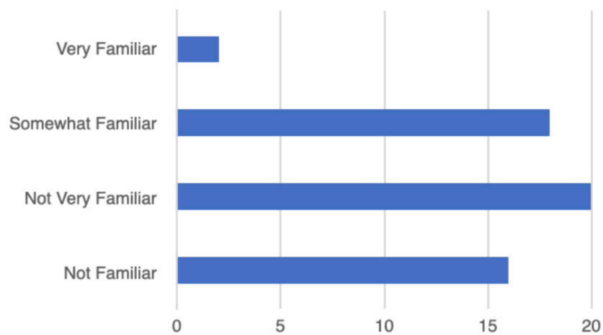


Figure 5

Understanding of the Potential Applications of AI in External School Evaluation Processes



Several respondents highlighted how AI could enhance efficiency and consistency in evaluations. In the open-ended survey response, seventeen participants saw value in AI for analysing large datasets, 8 participants recognised AI's potential in automating report writing and editing, and seven believed AI could assist in predicting future school performance and provide personalised recommendations. In interviews, evaluators with higher familiarity viewed AI as a valuable tool for improving efficiency and consistency in tasks such as report writing and data analysis. Evaluator_6 highlighted how AI could streamline report generation and ensure consistency across evaluations. However, evaluators with low familiarity were uncertain about its usefulness. Evaluator_1 mentioned, "My analysis skills are really good ... maybe I do not know how better it [AI] is than me."

While there is a general recognition of AI's potential usefulness, actual appreciation of its benefits correlates with the evaluators' familiarity and experience with AI tools. Those with more exposure to AI are more likely to perceive it as beneficial.

Barriers and Ethical Challenges in AI Adoption

The study identified key barriers that hinder the adoption of AI technologies among school evaluators.

Figure 6

"In the past three years, have you taken training in using digital technology for school external evaluation?"

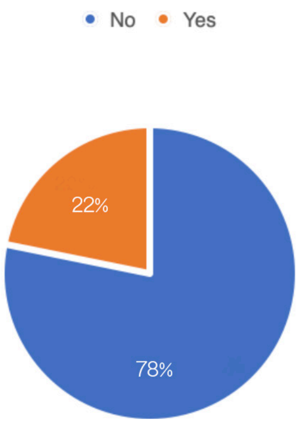
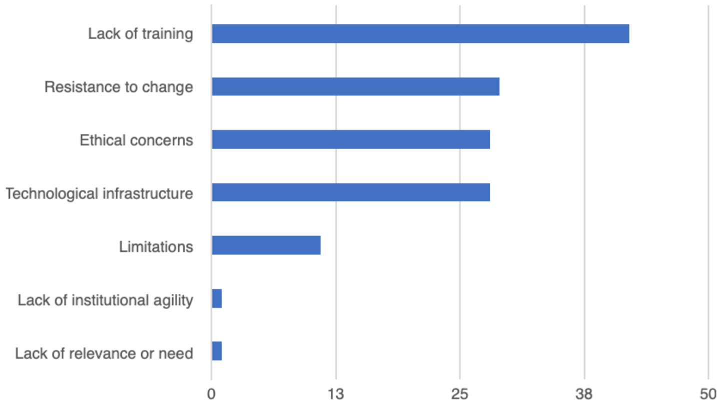


Figure 7

Barriers to AI Adoption in External School Evaluation



Participants reported significant barriers to adopting AI technologies in their evaluation processes. Lack of training was the most prominent barrier, with 43 participants identifying insufficient training as a significant obstacle. Thirty-five participants acknowledged resistance to change within organisations, indicating a cultural challenge in adopting new technologies. Thirty participants cited inadequate technological infrastructure, reflecting limitations in current systems to support AI integration. Thirty-five participants expressed ethical concerns regarding AI use.

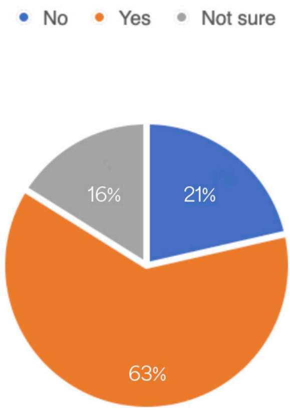
The need for professional development emerged as a critical theme. Evaluator_2 emphasised, “I would need training to understand better how it works, how it will help me carry out my work properly and how it might solve any challenges.” Organisational culture also posed challenges. Evaluator_3 noted, “I always work manually before and during the review ... I print everything, and even after, I write and type the report.” Infrastructure limitations were highlighted by Evaluator_4, who pointed out the need for “appropriate and up-to-date technological devices to effectively meet the requirements.” Data privacy concerns and ethical considerations were recurring themes in all interviews. Interviewees stressed the importance of human oversight to mitigate potential biases in AI-powered evaluations.

The predominant barriers to AI adoption are lack of training and resistance to change, compounded by infrastructural limitations and ethical concerns. Addressing these barriers is essential for facilitating AI integration in school evaluations.

When explicitly asked, 35 survey participants expressed significant ethical concerns about adopting AI in school evaluations.

Figure 8

Concern about Potential Ethical Issues or Fairness Implications Related to the Use of AI in School External Evaluation



Concerns about data privacy were significant, with 35 participants worried about risks related to handling sensitive student and school data using AI systems. The potential for AI algorithms to reinforce existing biases was a concern for 40 participants, reflecting apprehension about fairness and impartiality in AI-driven evaluations. A lack of transparency in AI decision-making processes made 30 participants feel uneasy and uncertain about how AI reaches conclusions.

Ethical considerations were also a significant theme in the interviews. Evaluator_5 warned, "If you do not train it correctly, you create stereotypes and bias, and you reinforce them." The need for transparency was highlighted by Evaluator_6, who commented, "openness and transparency around the use of data and how it is processed, I think would be the biggest concern". Evaluators, particularly those less familiar with AI, such as Evaluator_3 and Evaluator_4, mentioned a lack of trust in AI's ability to perform critical tasks accurately, which could hinder adoption. Data security was a concern for Evaluator_4, who expressed, "You are inputting very confidential and sensitive information. Who has access to that? How is that information being used?"

These findings indicate that evaluators are apprehensive about potential biases, data privacy, and the lack of transparency in AI systems. This highlights the need for robust ethical frameworks to address these issues. Addressing these concerns is crucial to building trust among evaluators and ensuring the fair and unbiased application of AI in school evaluation processes.

Integration of Technology in Current Evaluation Processes

This section assesses the current state of technology integration in school evaluations. The survey revealed that technology integration in evaluation processes is limited. Thirty-one participants reported no integration of digital technology in their evaluation practices. Twenty-four participants indicated partial integration, mainly using essential digital tools for administrative tasks. Only one participant reported full integration of digital technologies in their evaluation processes.

The limited use of technology was also evident in the interviews. Evaluator_2 mentioned, "We mainly use digital tools for scheduling and communication, not for evaluation tasks." However, there were signs of readiness for AI integration among those with higher technology use. Evaluator_5, who reported greater use of digital tools, stated, "We have all these indicators, and we have an algorithm every year, and we feed that algorithm all kinds of information on all the schools annually."

The limited integration of technology suggests that many evaluators are not currently positioned to adopt AI tools. This highlights the necessity for infrastructural improvements and organisational support for technology adoption in evaluation processes.

These findings address the research questions by highlighting the evaluators' awareness of AI, their perceptions of its ease of use and usefulness, and the barriers and ethical concerns that influence AI adoption in school evaluations. The insights gained set the stage for further discussion on how to facilitate the effective integration of AI in educational evaluation processes.

Discussion

The findings reveal moderate awareness and limited adoption of AI, with significant variations in perceived usefulness and ethical concerns. While there is optimism about AI's potential, substantial barriers remain. This section interprets these findings concerning the research questions, theoretical framework, and existing literature.

Awareness and Familiarity with AI

The moderate awareness and familiarity with AI among school evaluators, with only just under half (n=26) somewhat familiar and 15 participants unfamiliar, highlight a significant gap in exposure to AI. This aligns with Granić and Marangunić's (2019) observation that familiarity with AI in educational contexts is still developing, particularly in less common applications like external evaluation. While AI has been increasingly adopted in teaching and learning (Sprenger & Schwaninger, 2021), its role in external evaluations is far less explored. The gap in familiarity signals a critical need for targeted professional development, which aligns with Guan et al. (2020), who also found that a lack of understanding of AI's practical applications limits its broader use in education. As the TAM suggests, familiarity influences PEoU and PU, which are key components in whether evaluators will eventually adopt AI tools (Davis, 1989).

The analysis suggests that familiarity with AI is a key determinant of its perceived usefulness and ease of use for school evaluators. Those with more exposure to AI-powered tools tend to view it more favourably, recognising its potential to improve efficiency and consistency in educational evaluations. The low integration rates may reflect concerns about the complexity and effort required to use AI tools effectively. Addressing these concerns through user-friendly technology design and comprehensive training could facilitate higher adoption rates.

Perceived Usefulness and Integration of AI

Most participants (n=32) expressed that AI could improve the efficiency and accuracy of school evaluation processes, particularly in data analysis and report generation. This finding aligns with the TAM, which posits that PU is a core determinant of technology adoption (Venkatesh & Davis, 2000). Evaluators recognise the potential of AI to enhance data-driven decision-making and streamline processes, consistent with Holmes et al. (2019), who noted AI's ability to manage and process vast amounts of data in educational settings. These findings support the notion that AI can streamline various aspects of the evaluation process, reducing the workload on evaluators and enabling more data-driven decision-making. The ability of AI to handle large datasets and provide detailed analysis can significantly enhance the quality and reliability of evaluations.

Despite recognising its usefulness, the actual integration of AI into evaluations remains minimal, with more than half of the participants reporting no integration. This gap is similar to what Harford (2018) noted in Ofsted's initial efforts to digitise its evaluation processes. The limited integration suggests that even when evaluators understand AI's value, practical implementation is hindered by infrastructural constraints and a lack of tailored AI tools for external evaluations (Selwyn, 2019). This is compounded by institutional and staff resistance to change. Addressing these barriers is key for actual adoption.

Barriers to AI Adoption and Implications

Resistance to change was a significant barrier mentioned by the study's participants. This reflected the challenges outlined by Rogers's (2003) diffusion of innovations theory regarding how established norms can impede the adoption of new technologies. Moreover, the study found that lack of training, ethical concerns, and inadequate technological infrastructure are other main barriers to AI adoption in school evaluations. These findings are consistent with Alharbi and Drew (2014), who identified similar barriers to technology integration in educational settings.

Training

Lack of training emerged as the most significant barrier, with 43 participants indicating that in the past 3 years, they had not received formal training on digital technologies like AI. This aligns with findings by Granić & Marangunić (2019), who emphasised that insufficient training often slows technology adoption. Without proper training, evaluators may struggle to understand the full potential of AI and feel uncertain about integrating it into their workflows, negatively affecting their PEoU and PU (Davis, 1989). As Marikyan & Papagiannidis (2024) suggest, targeted training focusing on both the technical aspects and practical applications can enhance evaluators' competence and confidence in using AI-powered tools.

Educational policymakers and leaders should prioritise the development of tailored training that focuses on increasing AI competence among evaluators. Such programmes should cover the technical aspects of AI tools and emphasise their practical applications in the context of school evaluations, as outlined by Guan et al. (2020), thereby enhancing PEoU and PU and fostering adoption.

Investment in Infrastructure

Inadequate technological infrastructure, including both hardware and software, underscores the practical limitations inspectorates face. Guan et al. (2020) mirrored this, pointing to the need for more investment in technological infrastructure to support AI adoption in educational contexts. Selwyn (2019) noted that technology adoption remains unlikely without adequate resources. Evaluators cannot effectively use AI tools without the necessary hardware, software, and support systems.

Policymakers, inspectorates, and technology developers should invest in upgrading technological infrastructure to support AI integration. Ensuring that evaluators have access to necessary technologies will enhance PU and facilitate adoption, aligning with TAM's assertion that external factors influence technology adoption.

Ethical Concerns

Ethical considerations were significant, with most participants concerned about data privacy, potential biases and lack of transparency in AI systems. Participants were concerned that AI systems could inadvertently reinforce existing inequalities, mainly if they rely on biased historical data (Morley et al., 2020). Additionally, the opacity of AI decision-making processes undermines trust (Araujo et al., 2020; Selwyn, 2021).

Robust ethical frameworks must be developed to address these concerns (Morley et al., 2020). Aligning AI implementation with policies like the EU AI Act (2024) can mitigate ethical issues. Transparency, accountability, and fairness must be integral to AI systems to build trust among evaluators. Addressing ethical concerns will be critical to the successful adoption of AI in school evaluations.

Limitations of the Study

Despite the valuable insights provided by this study, there are specific limitations. First, the relatively small and uneven sample size may limit the generalisability of the findings across inspectorates. Second, the cross-sectional design provides a snapshot in time, not accounting for evolving perceptions. Third, reliance on online translations and potential language barriers could have affected the accuracy of responses. Lastly, the fast-paced development of AI means new tools and policies may have emerged since data collection. Future research should consider larger, more diverse samples, employ longitudinal designs, and incorporate professional translation services to enhance the validity and applicability of these findings.

Implications

This study extends the TAM by highlighting the significant role of ethical concerns as external variables influencing technology adoption in the context of AI integration in education. Incorporating ethical considerations into the TAM framework may provide a more comprehensive understanding of adoption factors.

For policymakers and educational leaders, the findings underscore the necessity of investing in training programs, infrastructural improvements, and ethical guidelines to facilitate AI adoption. The potential benefits of AI in enhancing evaluation processes can be realised by addressing barriers such as lack of training and ethical concerns.

Addressing the identified barriers through strategic interventions can enhance evaluators' adoption of AI, leading to improved efficiency and effectiveness in external school evaluations. Stakeholders can fully leverage AI's potential by investing in training, infrastructure, and ethical considerations. These efforts will contribute to improving school evaluation practices and educational outcomes.

Conclusion

This study highlights both enthusiasm and trepidation toward AI among European school evaluators. The findings reveal moderate awareness and adoption of AI. Rooted in the TAM, the study shows how perceived usefulness, ease of use and ethical safeguards shape evaluators' readiness to adopt AI. The results underscore the importance of comprehensive training, infrastructural development, and robust ethical frameworks to address evaluators' concerns about data privacy and bias.

By embracing targeted professional development and mindful policy creation, inspectorates and educational authorities can unlock AI's potential for enhancing school evaluations. As technology advances rapidly, continued empirical investigation will be vital, enabling stakeholders to refine best practices, mitigate risks, and ultimately ensure that AI tools support fair, transparent, and effective educational outcomes across Europe.

Notes on Contributor

Keith Aquilina specializes in digital education and quality assurance with over two decades in education. He holds a Master's in Online and Distance Education from Open University, UK, and a diploma in computing in education. An expert in the European Commission's IFREG advisory group, he serves as a digital evaluator with MFHEA and a visiting lecturer with IfE.

References

Al-Adwan, A. S., Li, N., Al-Adwan, A., Abbasi, G. A., Albelbisi, N. A., & Habibi, A. (2023). Extending the Technology Acceptance Model (TAM) to Predict University Students' Intentions to Use Metaverse-Based Learning Platforms. Education and Information Technologies, 28(11), 15381–15413. https://doi.org/10.1007/S10639-023-11816-3

Alharbi, S., & Drew, S. (2014). Using the technology acceptance model in understanding academics' behavioural intention to use learning management systems. International Journal of Advanced Computer Science and Applications, 5(1), 143–155. https://thesai.org/publications/viewpaper?volume=5&issue=1&code=ijacsa&serialno=20

Araujo, T., Helberger, N., Kruikemeier, S., & de Vreese, C. H. (2020). In AI we trust? Perceptions about automated decision-making by artificial intelligence. AI & Society, 35(3), 611–623. https://doi.org/10.1007/s00146-019-00931-w

Baxter, J., & Ehren, M. (2014, July 14). Lessons from Europe on how best to inspect schools. The Conversation. https://theconversation.com/lessons-from-europe-on-how-best-to-inspect-schools-28638

Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. Qualitative Research in Psychology, 3(2), 77–101. https://doi.org/10.1191/1478088706qp063oa

Bryk, A. S., Gomez, L. M., Grunow, A., & LeMahieu, P. G. (2015). Learning to Improve: How America's Schools Can Get Better at Getting Better. Harvard Education Press.

Chen, L., Chen, P., & Lin, Z. (2020). Artificial Intelligence in Education: A Review. IEEE Access, 8, 75264–75278. https://doi.org/10.1109/ACCESS.2020.2988510

DataGuidance. (2023). Netherlands: AP publishes advice regarding AI supervision in education. https://www.dataguidance.com/news/netherlands-ap-publishes-advice-ai-supervision

Davis, F. D. (1989). Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology. MIS Quarterly, 13(3), 319–340. https://doi.org/10.2307/249008

Department for Education. (2023). School inspection handbook for September 2023. GOV.UK. https://www.gov.uk/government/publications/school-inspection-handbook-eif/school-inspection-handbook-for-september-2023

Ehren, M., & Baxter, J. (2021). Trust, capacity and accountability: A triptych for improving learning outcomes. In M. Ehren & J. Baxter (Eds.), Trust, accountability and capacity in education system reform (pp. 288–304). Routledge. https://doi.org/10.4324/9780429344855-14

European Commission. (2025). AI Act | Shaping Europe's digital future. https://digital-strategy.ec.europa.eu/en/policies/regulatory-framework-ai

European Commission. (2020). Digital Education Action Plan (2021-2027): Resetting education and training for the digital age. https://ec.europa.eu/education/education-in-the-eu/digital-education-action-plan_en

European Education and Culture Executive Agency (Eurydice). (2019). Digital education at school in Europe A. Bourgeois, P. Birch, & O. Davydovskaia, contributors. Publications Office. https://data.europa.eu/doi/10.2797/339457

Fullan, M., & Langworthy, M. (2014). A Rich Seam: How New Pedagogies Find Deep Learning. Pearson. http://www.michaelfullan.ca/wp-content/uploads/2014/01/3897.Rich_Seam_web.pdf

Granić, A. (2022). Educational Technology Adoption: A systematic review. Education and Information Technologies, 27(7), 9725. https://doi.org/10.1007/S10639-022-10951-7

Granić, A., & Marangunić, N. (2019). Technology acceptance model in educational context: A systematic literature review. British Journal of Educational Technology, 50(5), 2572–2593. https://doi.org/10.1111/BJET.12864

Greatbatch, D., & Tate, S. (2019). School improvement systems in high performing countries. Department for Education, UK. https://assets.publishing.service.gov.uk/media/5f22d5f98fa8f57ac683d827/School_improvement_systems_in_high_performing_countries.pdf

Guan, C., Mou, J., & Jiang, Z. (2020). Artificial intelligence innovation in education: A twenty-year data-driven historical analysis. International Journal of Innovation Studies, 4(4), 134–147. https://doi.org/10.1016/J.IJIS.2020.09.001

Guthrie, S., Wamae, W., Diepeveen, S., Wooding, S., & Grant, J. (2013). Measuring research: A guide to research evaluation frameworks and tools. Santa Monica, CA: RAND Corporation. https://www.rand.org/pubs/monographs/MG1217.html

Harford, S. (2018, September 7). Ofsted is going digital! Ofsted Blog.https://educationinspection.blog.gov.uk/2018/09/07/ofsted-is-going-digital/

Holmes, W., Bialik, M., & Fadel, C. (2019). Artificial Intelligence in Education: Promises and Implications for Teaching and Learning. Center for Curriculum Redesign. http://curriculumredesign.org/wp-content/uploads/AIED-Book-Excerpt-CCR.pdf

Joint Research Centre [JRC]. (2023). The future of technology in education: Trends and scenarios. European Commission. https://joint-research-centre.ec.europa.eu/jrc-news-and-updates/future-technology-education-trends-and-scenarios-2023-12-01_en

Kooser, A. (n.d.). How Does Technology Improve a Business? Chron. http://smallbusiness.chron.com/technology-improve-business-2188.html

Lin, Y., & Yu, Z. (2023). Extending Technology Acceptance Model to higher-education students' use of digital academic reading tools on computers. International Journal of Educational Technology in Higher Education, 20(1), 1–24. https://doi.org/10.1186/S41239-023-00403-8/TABLES/6

Lynch, L. (2023). AI in Education: Introduction. Britannica Education. https://britannicaeducation.com/blog/ai-in-education/

MacBeath, J. (2019). The future of the teaching profession (2nd ed.). Education International.

Marangunić, N., & Granić, A. (2015). Technology acceptance model: A literature review from 1986 to 2013. Universal Access in the Information Society, 14(1), 81–95. https://doi.org/10.1007/s10209-014-0348-1

Marikyan, D., & Papagiannidis, S. (2024). Technology Acceptance Model. Theory Hub. https://open.ncl.ac.uk/theories/1/technology-acceptance-model/

Martínez-Serrano, M. del C., Romero-García, M. A., García-Martínez, I., & Gavín-Chocano, Ó. (2023). Inspection Digital Literacy for School Improvement. European Journal of Investigation in Health, Psychology and Education, 13(4), 701-717. https://doi.org/10.3390/ejihpe13040053

Morley, J., Floridi, L., Kinsey, L., & Elhalal, A. (2020). From what to how: An initial review of publicly available AI ethics tools, methods and research to translate principles into practices. Science and Engineering Ethics, 26(4), 2141–2168. https://doi.org/10.1007/s11948-019-00165-5

OECD. (2023). OECD Digital Education Outlook 2023: Towards an Effective Digital Education Ecosystem. OECD Publishing. https://doi.org/10.1787/c74f03de-en

OECD. (2020). Developing a school evaluation framework to drive school improvement. OECD Publishing. https://doi.org/10.1787/60b471de-en

OECD (2015), Education at a Glance 2015: OECD Indicators, OECD Publishing, Paris, http://dx.doi.org/10.1787/eag-2015-en.

OECD (2013), Synergies for Better Learning: An International Perspective on Evaluation and Assessment, OECD Reviews of Evaluation and Assessment in Education, OECD Publishing, Paris, https://dx.doi.org/10.1787/9789264190658-en.

Ofsted. (2024). Technology requirements to contract as an Ofsted inspector. GOV.UK. https://www.gov.uk/guidance/technology-requirements-to-contract-as-an-ofsted-inspector

Rogers, E. (2003). Diffusion of Innovations (5th ed.). Simon and Schuster.

Rogers, R. H. (2018). Coding and writing analytic memos on qualitative data: A review of Johnny Saldaña's the coding manual for qualitative researchers. The Qualitative Report, 23(4), 889-892. https://doi.org/10.46743/2160-3715/2018.3459

SafetyStratus. (n.d.). Inspections and observations: Tech improvements. SafetyStratus. https://www.safetystratus.com/blog/simple-ways-technology-improves-inspections-and-observations/

Schepers, J. J. L., & Wetzels, M. (2007). A meta-analysis of the technology acceptance model: Investigating subjective norm and moderation effects. Information & Management, 44(1), 90–103. https://doi.org/10.1016/j.im.2006.10.007

Scherer, R., Siddiq, F., & Tondeur, J. (2019). The Technology Acceptance Model (TAM): A meta-analytic structural equation modelling approach to explaining teachers' adoption of digital technology in education. Computers & Education, 128, 13–35. https://doi.org/10.1016/j.compedu.2018.09.009

Selwyn, N. (2016). Education and Technology: Key Issues and Debates. Bloomsbury Publishing.

Selwyn, N. (2019). Should Robots Replace Teachers? AI and the Future of Education. Polity Press.

Selwyn, N. (2021). The risks of data-driven education. British Educational Research Journal, 47(6), 1333–1348. https://doi.org/10.1002/berj.3715

SICI. (n.d.). The Role of Inspectorates Across Europe. Retrieved 21 December 2023, from https://www.sici-inspectorates.eu/activities/development-and-research/research/the-role-of-inspectorates-across-europe

Sprenger, D. A., & Schwaninger, A. (2021). Technology acceptance of four digital learning technologies (classroom response system, classroom chat, e-lectures, and mobile virtual reality) after three months' usage. International Journal of Educational Technology in Higher Education, 18(1), 1–17. https://doi.org/10.1186/S41239-021-00243-4/TABLES/5

Terry, G., Hayfield, N., Clarke, V., & Braun, V. (2017). Thematic analysis. The SAGE handbook of qualitative research in psychology, 2nd Edition. London: Sage, 17-37. https://doi.org/10.4135/9781526405555

UNESCO. (2019). Artificial Intelligence in Education: Challenges and Opportunities for Sustainable Development. UNESCO Publishing. https://unesdoc.unesco.org/ark:/48223/pf0000366994

Vate-U-Lan, P. (2020). A systematic review of artificial intelligence in education during 2000–2018. In M. H. Miraz, P. S. Excell, A. Ware, S. Soomro, & M. Ali (Eds.), Emerging Technologies in Computing (pp. 105–115). Springer, Cham. https://doi.org/10.1007/978-3-030-60036-5_11

Venkatesh, V., & Bala, H. (2008). Technology Acceptance Model 3 and a Research Agenda on Interventions. Decision Sciences, 39(2), 273–315. https://doi.org/10.1111/j.1540-5915.2008.00192.x

Venkatesh, V. & Davis, F.D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. Management Science, 46, 186–204. https://doi.org/10.1287/mnsc.46.2.186.11926

Vomberg, A., & Klarmann, M. (2022). Crafting survey research: A systematic process for conducting survey research. In C. Homburg, M. Klarmann, & A. Vomberg (Eds.), Handbook of Market Research (pp. 67–119). Springer. https://doi.org/10.1007/978-3-319-57413-4_4

Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education – where are the educators? International Journal of Educational Technology in Higher Education, 16(1), 39. https://doi.org/10.1186/s41239-019-0171-0