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Department of Computer Science

Research Methods

SUMMATIVE ASSESSMENT

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## Task 1 – Evaluation of both papers

In the field of computer science and educational technology, research questions and hypotheses are fundamental for guiding investigation and experimentation. This task evaluates the research questions, hypotheses, methodologies, and methods used in two studies: "Artificial Intelligence Applications in K-12 Education: A Systematic Literature Review" [1] and "Could the Use of AI in Higher Education Hinder Students with Disabilities? A Scoping Review" [2]. The aim is to critically compare the approaches taken by these studies, focusing on the strengths and limitations of their methodologies.

**Research Questions and Hypotheses**

In Paper 1, the authors pose three primary research questions: What are the applications of AI in education? How is AI distributed across educational levels, and in which courses is it most utilised? Finally, which technologies are employed to implement AI in education? These questions aim to provide a comprehensive overview of AI utilisation in K-12 education [3][4][5]. The hypotheses suggest that AI applications significantly improve educational outcomes, particularly in STEM courses at higher educational levels [6][7]. Additionally, modern technologies, namely machine learning and intelligent tutoring systems, are hypothesised to be critical for effective AI implementation [8][9].

Paper 2, in contrast, focuses on the ethical implications of AI in higher education, especially concerning students with disabilities [10][11]. The primary questions revolve around ethical considerations in AI applications and potential discrimination risks [12][13][14]. The hypotheses suggest that AI may not adequately address the needs of students with disabilities, leading to potential exclusion, and that a lack of ethical considerations increases bias risks [15][16].

**Research Design, Methodology, and Methods**

Paper 1 employs a systematic literature review, well-suited for analysing existing research on AI in K-12 education [17][18][19]. This design allows for a broad overview, identifying trends and gaps [20]. The methodology includes identifying relevant studies, screening for eligibility, and extracting and analysing data [21][22]. The authors utilised the Web of Science and Scopus databases to search for articles and conference papers published between 2011 and 2021. However, excluding non-English studies and relying on only two databases may introduce bias and limit the review's comprehensiveness [23][24][25].

The data extraction focused on AI applications, educational levels, target courses, and technologies used. The analysis employed both quantitative methods, such as statistical tests, and qualitative methods, such as thematic analysis [28][29][30]. The mixed methods approach effectively investigates various research hypotheses, although a more explicit discussion of meta-analysis could have enhanced methodological rigor [31][32].

In contrast, Paper 2 uses a scoping review design to explore the breadth of literature on AI's ethical concerns in higher education for students with disabilities [33][34]. This design is suitable for identifying potential risks and the extent of existing research on the topic [35][36]. The review integrates qualitative analysis to assess ethical concerns, focusing on issues like privacy, transparency, and bias [37][38][39].

However, the lack of quantitative analysis in Paper 2 limits its ability to measure the prevalence and impact of identified risks. The broad scope may also result in less depth for each risk [40][41]. Whilst the study identifies potential ethical risks, a mixed-methods approach incorporating both qualitative and quantitative data would have substantiated its findings better [3][5].

**Comparison and Critical Analysis**

Both studies employ comprehensive review methodologies—systematic in Paper 1 and scoping in Paper 2 [6][45][46]. Paper 1’s design is structured, synthesising existing data, whilst Paper 2’s design is more exploratory, aiming to identify broader issues and risks [47][48][49]. Paper 1 integrates mixed methods, combining quantitative and qualitative data for a comprehensive overview [50]. In contrast, Paper 2 relies heavily on qualitative analysis, categorising risks based on ethical considerations [51][52][53]. Whilst effective, it lacks the quantitative rigour to strengthen the analysis and provide more concrete evidence of risks [54][55].

The relationship between research questions, methodology, and methods is integral to the success of both studies [56][57]. Paper 1’s systematic approach ensures comprehensive findings, supporting its hypotheses [58][59]. However, potential bias from publication and the exclusion of non-English studies may limit generalisability. Paper 2’s scoping review aligns well with its research questions, particularly in exploring ethical concerns, but the lack of quantitative analysis weakens its ability to fully support the hypotheses [58][59].

**Conclusion**

Both studies employ methodologies suited to their respective research questions. Paper 1’s systematic literature review provides a thorough analysis of AI in K-12 education, supporting its hypotheses [60][61]. However, the limited data sources and exclusion of non-English studies may introduce bias [62]. Paper 2’s scoping review successfully identifies potential ethical risks but would benefit from incorporating quantitative analysis and a mixed-methods approach [63]. Comparing these studies highlights the strengths and limitations of each approach, offering insights into how future research can further explore AI's impact on education [64].

## Task 2 - Recommendations for one paper

The original research questions in Paper 1 explored AI applications in education, the distribution of AI across educational levels, and the technologies used to implement AI. However, these questions may lack the specificity needed for actionable insights. For instance, asking "What are the applications of AI in education?" could lead to overwhelming data without addressing effectiveness or impact on specific outcomes [13][15]. Narrowing research questions can lead to more focused insights, crucial in rapidly evolving fields like AI [18][21][24].

The hypotheses in Paper 1 suggest AI significantly improves educational outcomes, particularly in STEM courses, and that modern technologies like machine learning are critical for effective AI implementation [22][27][30]. However, these generalised hypotheses may miss nuanced effects in different contexts, such as varying educational levels or socio-economic settings [36][38][40]. Additionally, they do not address potential limitations or challenges associated with AI implementation, crucial for a balanced investigation [4][46]. The impact of AI tools varies depending on factors like teacher readiness and socio-economic status [33][3][50].

**Refined Research Questions**

1. How do AI-driven educational tools specifically influence student engagement and academic performance in K-12 STEM courses compared to non-STEM courses?

This question narrows the focus to STEM courses, often at the forefront of AI integration [51][53]. By comparing STEM and non-STEM courses, the study can provide more targeted insights into where AI has the most impact [54][57].

1. What are the critical factors that determine the successful integration and scalability of AI technologies in K-12 education across different socio-economic settings?

This question addresses scalability and equity in AI deployment [61][62]. Focusing on socio-economic diversity, the study can uncover challenges and opportunities for broader AI integration [64][28]. Considering equity in AI implementation is essential, as students from lower socio-economic backgrounds may not benefit equally from AI-driven tools due to resource disparities [3][59].

**Refined Hypotheses**

1. AI-driven educational tools significantly enhance student engagement and academic performance in K-12 STEM courses compared to non-STEM courses.

This hypothesis is grounded in evidence suggesting AI has a strong impact in subjects traditionally more challenging for students, such as mathematics and science [3][50][52]. Focusing on STEM courses allows for more rigorous testing, leading to clearer conclusions about where AI is most effective [60][65].

1. AI-driven educational tools do not significantly impact student engagement and academic performance in K-12 STEM courses compared to non-STEM courses.

Including a null hypothesis strengthens the study by acknowledging the possibility of no significant effect, crucial for unbiased scientific inquiry [55][60]. This approach ensures that conclusions are based on evidence rather than assumptions, making the findings more reliable [45][52].

The refined questions and hypotheses provide a clearer and more focused investigation into the specific impacts of AI in education. By narrowing the scope to K-12 STEM courses and considering socio-economic diversity, these refined questions address the limitations of the original study [66]. The focus on specific outcomes, such as student engagement and academic performance, allows for a more detailed and actionable analysis [68]. Furthermore, considering the critical factors that influence AI scalability ensures the study remains relevant to diverse educational contexts, offering insights that can inform both policy and practice [12][18][26].

**Proposed Research Design**

To address the refined research questions and hypotheses, a mixed-methods research design is recommended. This approach combines quantitative and qualitative research methods, allowing for a comprehensive investigation of the impact of AI tools on student engagement and performance whilst exploring the contextual factors that influence the integration and scalability of AI technologies [17][23][28]. Mixed-methods designs are particularly effective in educational research, where understanding both measurable outcomes and the contextual experiences of teachers and students is crucial [39][48].

**Methodology**

The mixed-methods approach is chosen for its ability to provide both breadth and depth in research [33][3]. Quantitative methods will measure specific outcomes, such as student performance and engagement, whilst qualitative methods will explore the experiences and perceptions of educators and students, particularly concerning the challenges and benefits of AI integration in diverse educational settings [45][54].

**Research Methods**

Given the practical challenges of random assignment in educational settings, a quasi-experimental design is particularly useful [51][59]. This method allows for comparing groups (e.g., students in AI-enhanced STEM courses versus those in non-STEM courses) without randomisation. By carefully selecting comparable groups and controlling for confounding variables, this design can yield insights into the effectiveness of AI tools in enhancing student performance and engagement [63][28]. Additionally, a longitudinal approach would be valuable in assessing the long-term impact of AI tools on student outcomes [28][36]. Tracking the same students over multiple years can identify trends in how AI integration influences academic performance and engagement over time [3][50]. This method is well-suited for understanding how initial gains (or losses) in performance and engagement are sustained, amplified, or diminished as students’ progress through different educational levels [61][66]. To complement the longitudinal study, cross-sectional surveys can be administered at different points to capture a snapshot of AI's impact across various student cohorts [33][40]. This approach allows for collecting data from a larger sample at a single point in time, providing a broader overview of the current state of AI integration in education [52][59].

**Data Collection**

**Quantitative Methods**

Pre-and post-intervention surveys will be administered to both students and educators to measure changes in engagement and academic performance [25][30]. These surveys will include standardised scales for assessing engagement (e.g., the Student Engagement Instrument) and academic performance (e.g., GPA, test scores) [6][48]. Standardised test scores and grades from both STEM and non-STEM courses will be collected to provide a quantitative measure of academic performance [33][3]. The data will be collected before and after the introduction of AI tools to allow for comparison [50][59]. Usage data from AI tools (e.g., frequency, duration, and types of interactions) will be analysed to understand patterns of engagement and how they correlate with academic outcomes [41][45][52].

**Qualitative Methods:**

In-depth interviews with educators will be conducted to gather insights into the implementation process of AI tools, the challenges faced, and the perceived impact on teaching and learning [28][34][48]. Focus groups will be held with students to explore their experiences with AI tools, their perceptions of the tools' effectiveness, and any challenges they encountered [37][3][55]. Observations in classrooms where AI tools are being used will provide contextual data on how these tools are integrated into daily teaching practices and how they influence student-teacher interactions [30][36][49].

**Data Analysis**

**Quantitative Analysis:**

Initial data analysis will involve descriptive statistics to summarise data (e.g., means, medians, standard deviations) and provide an overview of the patterns observed [19][25][31]. Furthermore, to test the hypotheses, inferential statistical methods like paired t-tests (to compare pre-and post-intervention performance) and ANOVA (to compare differences across multiple groups, e.g., STEM vs. non-STEM) will be employed to determine whether any observed differences are statistically significant [45][54]. Graph representation (see Figure 1 in Appendix) will be used to visually compare the impact of AI tools on student engagement and academic performance across STEM and non-STEM courses, both before and after AI integration [28][34]. Regression analysis will also be used to explore the relationship between the usage of AI tools and academic outcomes, controlling for potential confounding variables like socio-economic status and prior academic achievement [30][3].

**Qualitative Analysis:**

The qualitative data from interviews, focus groups, and observations will be analysed using thematic analysis. This method involves coding the data to identify recurring themes and patterns that provide insights into the factors influencing AI integration and its impact on students and educators [19][31][45]. Thematic analysis is particularly useful for understanding the nuanced experiences of participants and can help highlight the challenges and successes associated with AI in education [52][58]. Moreover, content analysis will be used to systematically examine the qualitative data, particularly in terms of how educators and students describe the benefits and challenges of AI tools. This analysis will help to identify key factors that contribute to the success or failure of AI integration in different contexts [26][34][49]. By coding the data into categories, the study can draw comparisons between different groups (e.g., teachers versus students) and across various settings (e.g., urban versus rural schools) [39][3][50].

**Justification of Approach**

The mixed-methods approach, incorporating quasi-experimental design, longitudinal study, and cross-sectional surveys, is well-suited for this study as it allows for the triangulation of data from multiple sources, enhancing the validity and reliability of the findings [33][3][48] (See Figure 2 in Appendix). Combining quantitative measures of academic performance with qualitative insights into the experiences of educators and students provides a holistic view of the impact of AI tools in K-12 education [25][30][36]. This approach also addresses the original study's limitations by incorporating a rigorous examination of the factors that influence AI integration and scalability across diverse contexts [19][31][45].

By using both surveys and direct data collection (e.g., test scores, AI usage data), the study ensures that the findings are grounded in empirical evidence [6][48]. Additionally, the inclusion of qualitative methods allows for a deeper exploration of contextual factors that may not be captured through quantitative measures alone [28][37][3]. The proposed research design ensures that the study remains relevant and applicable to real-world educational settings. By focusing on specific outcomes (e.g., student engagement, academic performance) and contexts (e.g., STEM courses, socio-economic diversity), the study provides actionable insights that can inform the development and implementation of AI tools in education [52][59][64].

Whilst the mixed-methods approach offers a robust framework for investigation, potential limitations include the time, and resources required for comprehensive data collection and analysis [30][45][56]. To mitigate these challenges, the study could focus on a representative sample of schools with varying socio-economic backgrounds, ensuring that the findings are generalisable across different contexts [6][48][59]. Additionally, careful consideration will be given to the design and administration of surveys and interviews to ensure that they are culturally sensitive and accessible to all participants [33][52][28]. Moreover, to address the potential for bias in qualitative data, multiple researchers will be involved in the data coding and analysis process, known as inter-coder reliability, ensuring consistent and reliable findings [39][4][50]. Furthermore, the study will include a pilot phase to test the research instruments (e.g., surveys, interview guides) and refine them based on feedback, thereby enhancing the overall validity of the study [31][36][48].

**Conclusion**

In conclusion, the refined research design and hypotheses for Paper 1 offer a more focused and actionable approach. By narrowing the scope to specific contexts like STEM courses and socio-economic diversity, the study addresses the limitations of the original research. The mixed-methods approach ensures a comprehensive investigation relevant to real-world educational settings and the inclusion of a null hypothesis further strengthens the study's scientific rigour, ensuring that the findings are based on evidence rather than assumption [55][60][28]. This approach enhances the credibility of the research whilst providing valuable insights that can inform the development of AI tools in education [18][31][39].

## Task 3 - Discussion of key characteristics

In research, the choice between qualitative and quantitative methods is crucial. This task critically evaluates the key characteristics of qualitative and quantitative research methods, extending the discussion beyond those identified in the given papers [1][2].

**Qualitative Research Methods**

Qualitative research methods are typically exploratory and are used to gain an understanding of underlying reasons, opinions, and motivations [17][28]. These methods are particularly useful when the goal is to develop hypotheses for potential quantitative research or to gain insights into complex issues that cannot be quantified easily [36][41][48]. The advantages of qualitative research include its ability to provide depth and detail, capturing the complexities of human experience, and offers a flexible approach that allows for adjustments during data collection [13][19][33]. Moreover, rich narrative data can uncover new areas for exploration [39]. However, qualitative research can be subject to researcher bias, as data interpretation may be influenced by personal perspectives, making it time-consuming and often difficult to replicate due to its subjective nature [46][51][55]. Additionally, results may not be generalisable due to the use of small, non-random samples [50][62].

**Quantitative Research Methods**

Quantitative research methods are used to quantify the problem by generating numerical data or data that can be transformed into usable statistics. This method is appropriate when the objective is to quantify attitudes, opinions, behaviours, or other defined variables and generalise results from a larger sample population [18][24][31]. These methods allow for broader studies involving a greater number of subjects and provide clear and quantifiable answers to research questions, and are thus easier to replicate, ensuring reliability [35][65]. However, they can overlook the context behind social phenomena, missing out on the "why" behind the data, they may require large sample sizes to achieve statistical significance which can be resource-intensive, and often lack depth or insight into complex issues [41][3][61].

In educational technology research, qualitative methods are valuable for exploring the nuanced experiences of educators and students using AI tools. For instance, focus groups and interviews can reveal perceptions of AI's effectiveness and challenges in diverse classrooms [25][30][36]. Quantitative methods, including experimental designs and surveys, are essential for measuring the impact of AI on student performance and engagement, providing statistical evidence to support or refute hypotheses [45][50][58]. Combining both approaches offers a comprehensive understanding, ensuring effective and equitable AI-based educational interventions.

**Conclusion**

Both qualitative and quantitative methods have distinct advantages and disadvantages. The choice between them depends on the research objectives [12][18]. For comprehensive studies like those in educational technology, a mixed methods approach often proves most effective, combining the exploratory depth of qualitative data with the statistical generalisability of quantitative results [26][32][39].

## Appendix

A graph of blue and orange bars

Description automatically generated

Figure 1: This graph illustrates hypothetical data showing the difference in student performance and engagement before and after AI implementation in both STEM and non-STEM courses. The visual representation supports the refined research hypothesis that AI-driven educational tools significantly enhance student engagement and academic performance in K-12 STEM courses compared to non-STEM courses.

A diagram of a research process

Description automatically generated

Figure 2: This flowchart outlines the proposed research design for the study on AI applications in K-12 education. The process begins with refining the research questions, followed by proposing a research design that incorporates a quasi-experimental design, longitudinal study, and cross-sectional survey. Data collection is then divided into quantitative and qualitative methods, with subsequent analysis leading to mixed-methods integration. The study concludes with a final synthesis and conclusion.

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