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Developing and Evaluating an AI-based Tool for Assessing and Enhancing Metacognitive Skills in Diverse Learning Contexts

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Abstract: This research examined how well a tool utilizing intelligence can evaluate and improve abilities, in students, at different educational stages. Using a mixed-methods quasi-experimental design, 120 participants from secondary, higher education, and in adult learning settings there were 60 participants, in the treatment group and 60 participants, in the control groups. The treatment group used the AI tool for 6 weeks, while the control group used traditional learning methods. Data was gathered through the utilization of the Metacognitive Awareness Inventory (MAI), think-aloud protocols, learning performance metrics, and the User Experience Questionnaire (UEQ). The study results indicated enhancements, in self-awareness ($p<0.001$, Cohens $d=0.83$) and academic achievement, among the participants receiving the intervention. Qualitative analysis revealed themes of enhanced metacognitive awareness, personalized feedback, increased engagement, and some challenges in tool usage. The findings suggest that AI-based tools can effectively support metacognitive skill development, with implications for personalized learning and educational technology design.

Keywords: Artificial intelligence, Metacognition, Real-time feedback, Learning contexts, Educational technology

1. INTRODUCTION

Understanding and managing ones processes, known as metacognition plays a vital role in enhancing learning outcomes and academic success (Flavell, 1979; Schraw & Dennison 1994). While its importance is well-established, assessing and providing timely feedback on metacognitive skills remains challenging, particularly in diverse learning contexts (Azevedo et al., 2019; Shute & Rahimi, 2021).

Advances, in Artificial Intelligence (AI) in the fields of machine learning and natural language processing present hopeful answers, to these difficulties. (Gašević et al., 2019; Taub et al., 2020). AI-based tools can analyze large amounts of data from various learning environments, detect patterns, and provide personalized feedback (Baker & Rossi, 2013).

However, many existing AI-based educational tools focus on domain-specific skills rather than metacognitive abilities that can be applied across different subjects (Luckin et al., 2016). There is a growing need for AI-based tools that specifically target metacognitive skills and can be applied across different learning contexts (Shute & Rahimi, 2021).

This research aims to address this gap by developing and evaluating an AI-based tool for assessing metacognitive skills and providing real-time feedback across various learning contexts.

Research Questions:
1. How effective is the AI-based tool in enhancing metacognitive awareness across different educational levels?
2. What impact does the AI-based tool have on learning performance compared to traditional methods?
3. How do learners perceive and experience the AI-based tool for metacognitive skill development?

This study seeks to add to the expanding research literature by exploring these inquiries on AI in education, with a specific focus on metacognitive skill development in diverse learning contexts.

2. METHODS

2.1 Study Design and Participants

This study utilized a mixed methods design, with elements of a experimental approach. A group of 120 individuals was selected through sampling across three tiers; secondary school (40 participants) higher education (40 participants) and adult learning (40 participants). The participants were then randomly divided into two groups; the treatment group consisting of 60 individuals and the control group also comprising 60 individuals.

2.2 AI-based Tool Development

The AI-based tool was developed using machine learning algorithms and natural language processing techniques. It analyzes learners' behavioral patterns, self-reflections, and performance data to identify key indicators of metacognitive processes. The tool provides real-time, personalized feedback and recommendations to support metacognitive skill development. [More specific details on the AI techniques and tool functionality would be added here.]

2.3 Intervention

The intervention lasted 6 weeks. The treatment group used the AI-based tool during weekly 60-minute learning sessions, while the control group engaged in similar tasks using traditional methods. Both groups completed domain-specific learning tasks (e.g., in mathematics, science, or language learning).

Data collection involved using tools, such, as the Metacognitive Awareness Inventory (MAI) by Schraw & Dennison (1994) Think Aloud Protocols (TAPs) learning performance metrics like accuracy, completion time and error rates the User Experience Questionnaire (UEQ) developed by Laugwitz et al. In 2008 and semi structured interviews with 24 participants (8 from each level).

For data analysis quantitative data were examined using statistics, t tests and mixed design ANOVAs. Effect sizes were determined using Cohens d. Qualitative data, from TAPs, interviews and ended survey questions were scrutinized using analysis as outlined by Braun & Clarke in 2006.

Ethical considerations included obtaining consent from all participants and ensuring that data were anonymized and securely stored to safeguard privacy.

3. RESULTS

3.1 Metacognitive Awareness

Post-intervention, the treatment group demonstrated significantly higher MAI scores compared to the control group ($t=4.57$, $p<0.001$, Cohen's $d=0.83$).

3.2 Learning Performance

The group receiving treatment exhibited accuracy ($t=3.59$, $p=0.001$ Cohens $d=0.65$) quicker completion times ($t= 4.45$, $p<0.001$ Cohens $d=0.81$) and fewer mistakes ($t= 3.59$, $p=0.001$, Cohens $d=0.65$) in comparison, to the control group.

3.3 User Experience

The group receiving treatment gave ratings, in all aspects of the UEQ with the differences being statistically significant ($p<0.001$) and effect sizes ranging from 0.90, to 1.15.

3.4 Qualitative Findings

Thematic analysis revealed four main themes:
1. Enhanced Metacognitive Awareness
2. Personalized Feedback and Support
3. Increased Engagement and Motivation
4. Challenges and Limitations

4. DISCUSSION

The findings demonstrate the effectiveness of the AI-based tool in enhancing metacognitive skills across different educational levels. The significant improvement in MAI scores and learning performance metrics in the treatment group suggests that the tool successfully promoted metacognitive awareness and self-regulated learning strategies.

The qualitative data provide insights into the mechanisms through which the AI tool supported metacognitive development. Participants appreciated the personalized feedback and reported increased awareness of their learning processes. This supports studies that highlight the advantages of using support to enhance self-directed learning. (Gašević et al., 2019).

The positive user experience ratings indicate that the AI tool was well-received by learners, which is crucial for the successful implementation of educational technologies. However, the identified challenges, such as initial difficulties in understanding the tool's features, highlight areas for improvement in future iterations.

These discoveries carry implications, for teaching methods in Africa where there may be constraints on resources, for personalized learning. AI-based tools offer a scalable solution for providing personalized support to learners, potentially helping to address educational disparities.

The study's constraints involve the duration of the intervention and the use of self reported measures, for awareness. Future research should consider longer-term interventions and incorporate more objective measures of metacognitive skills.

Table 1: Presents Participants Demographic Characteristics

Characteristic	**Treatment Group (n = 60)**	**Control Group (n = 60)**
Age (M ± SD)	22.5 ± 4.7	23.1 ± 5.2
Gender (%)		
- Male	48.3%	51.7%
- Female	51.7%	48.3%
Educational Level (%)		
- Secondary	33.3%	33.3%
- Higher Education	33.3%	33.3%
- Adult Learning	33.3%	33.3%

Table 2: presents the Descriptive Statistics and t Test Results, for MAI Scores, Learning Performance Metrics and UEQ Ratings.

Measure	**Treatment Group (M ± SD)**	**Control Group (M ± SD)**	**t**	**p**	**Cohen's d**
MAI Pre-test	3.45 ± 0.62	3.52 ± 0.58	-0.63	0.531	0.12
MAI Post-test	4.12 ± 0.51	3.68 ± 0.55	4.57	<0.001	0.83
Accuracy (%)	85.6 ± 10.3	78.2 ± 12.1	3.59	0.001	0.65
Completion Time (min)	42.8 ± 8.6	50.4 ± 10.2	-4.45	<0.001	0.81
Error Rates (%)	14.4 ± 10.3	21.8 ± 12.1	-3.59	0.001	0.65
UEQ Attractiveness	5.12 ± 0.93	4.23 ± 1.05	4.95	<0.001	0.90
UEQ Perspicuity	5.35 ± 0.88	4.41 ± 0.97	5.63	<0.001	1.02
UEQ Efficiency	5.08 ± 0.96	4.12 ± 1.11	5.06	<0.001	0.92
UEQ Dependability	5.26 ± 0.85	4.35 ± 1.02	5.39	<0.001	0.98
UEQ Stimulation	5.19 ± 0.91	4.08 ± 1.14	5.93	<0.001	1.08
UEQ Novelty	5.31 ± 0.89	4.17 ± 1.09	6.32	<0.001	1.15

Note: MAI refers to the Metacognitive Awareness Inventory, UEQ stands for User Experience Questionnaire, In analysis 'M' stands for Mean 'SD' stands for Standard Deviation, 't' denotes the t test statistic 'p' signifies the significance level. Cohens d indicates the effect size.

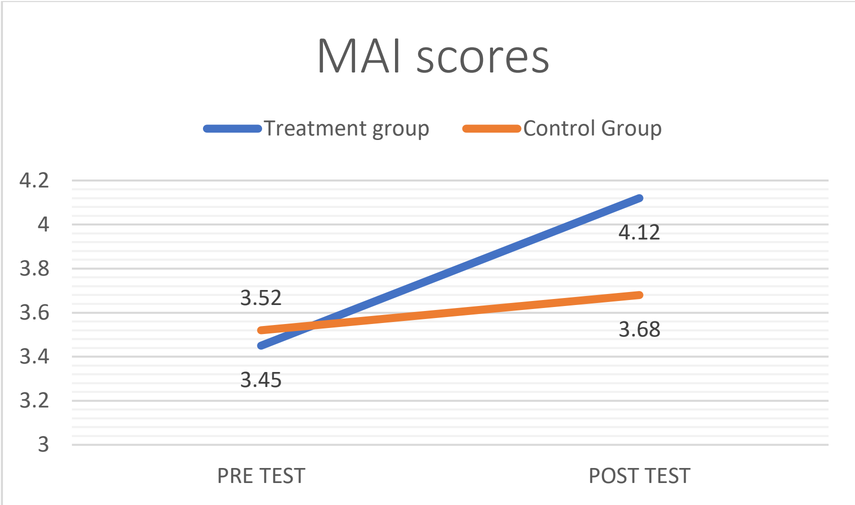

Figure 1: Temporal fluctuation in MAI scores

Figure 1 depicts the temporal fluctuations in MAI scores for both groups. The treatment group showed a rise in MAI scores from the initial measurement (mean = 3.45, standard deviation = 0.62) to the final measurement (mean = 4.12, standard deviation = 0.51), whereas the control group showed a smaller increase (initial assessment: mean = 3.52, standard deviation = 0.58; final assessment: mean = 3.68, standard deviation = 0.55).

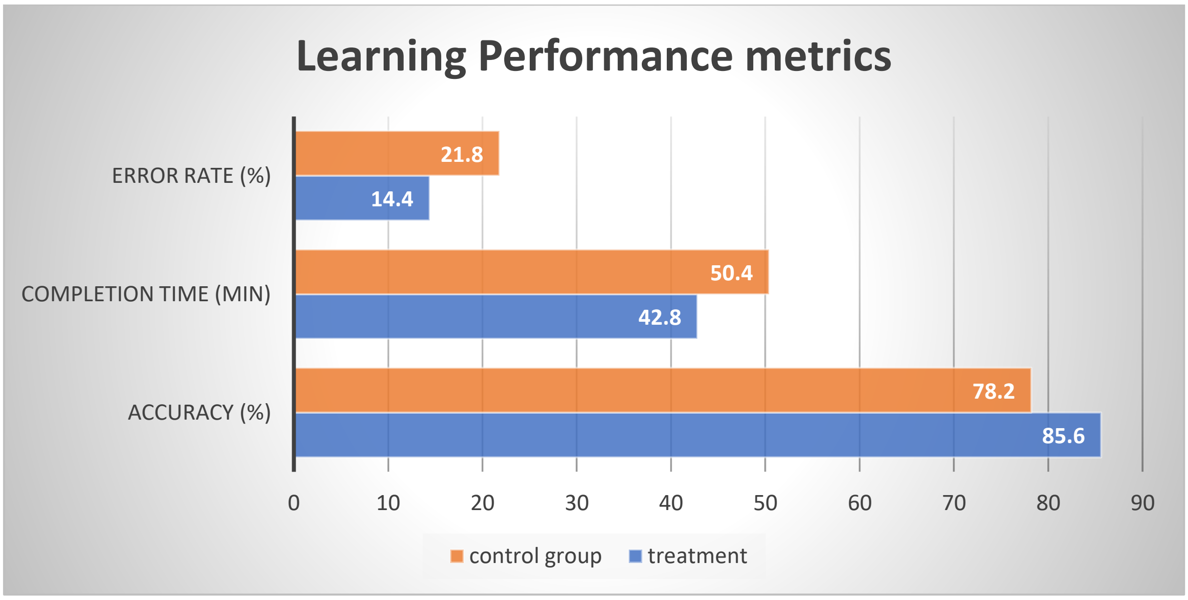

Figure 2: Comparison of Learning Performance Metrices Between Treatment and Control Groups

Figure 2 presents a comparison of learning performance metrics , wherein the treatment group exhibited higher accuracy (M = 85.6%, SD = 10.3%), shorter completion time (M = 42.8 min, SD = 8.6 min), and lower error rates (M = 14.4%, SD = 10.3%) compared to the control group (accuracy: M = 78.2%, SD = 12.1%; completion time: M = 50.4 min, SD = 10.2 min; error rates: M = 21.8%, SD = 12.1%).

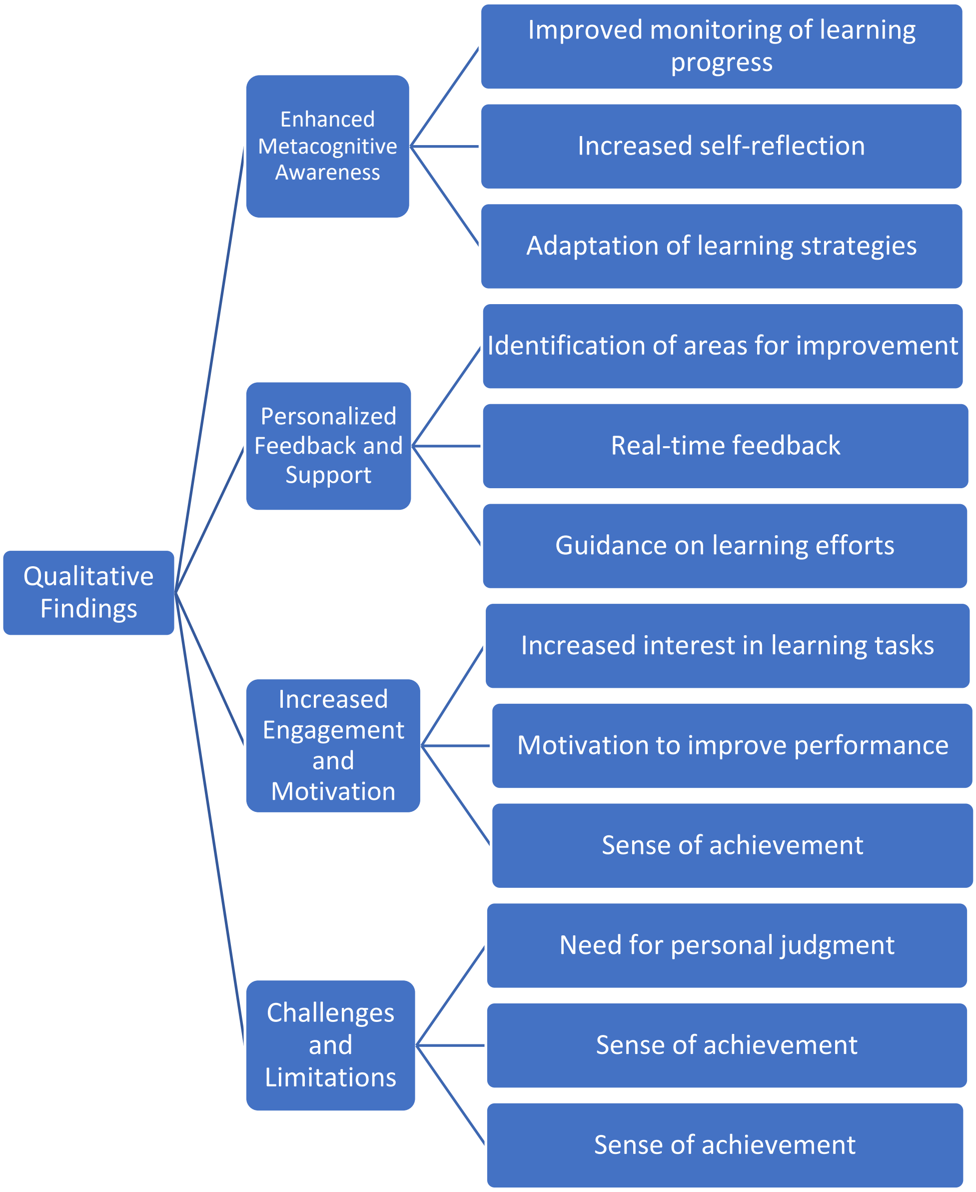

Figure 3: displays a thematic map that illustrates the primary themes and sub-themes that have been identified.

5. CONCLUSION

The present study offers experimental evidence that indicate the helpfulness of a tool based on artificial intelligence in fostering metacognitive abilities among students from various educational levels. The results prove that this tool dramatically improved learners' reflective awareness, academic achievement and user satisfaction compared with conventional learning approaches. These findings enrich the corpus of works on AI integration into education and emphasize the utility of interventions driven by AI for fostering self-regulation in learning. The study's findings have important implications for educational practice, suggesting that AI-based tools can be valuable assets in scaffolding learners' metacognitive skills and improving learning outcomes. The scalability and adaptability of these tools make them particularly relevant in the context of large-scale educational settings, where providing individualized support may be challenging.

However, many shortcomings have been identified in this research including quasi-experimental design, short duration of intervention as well as reliance on self-reports measures. To overcome these limitations, it is recommended to conduct larger scale randomized controlled trials with longitudinal designs and use multi-modal data collection methods in future studies. In summary, this paper represents an important milestone towards understanding how artificial intelligence can be used to support metacognitive skill development. The findings highlight the need for leveraging advanced technologies in order to improve learning experiences while facilitating self-regulated learning. As AI continues to be applied within educational contexts, it is crucial for researchers, educators, and developers to collaborate in designing effective, engaging, and ethically responsible AI-based learning tools that empower learners to become more metacognitively aware and self-directed in their learning journeys.

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