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COMPARATIVE ANALYSIS OF STUDENT ENGAGEMENT IN TRADITIONAL VS AI-ASSISTED LEARNING USING UWES-9S

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In this study, we empirically investigate the impact of AI-assisted learning environments versus traditional teaching methods on student engagement at the University of Montenegro. Using the Utrecht Work Engagement Scale for Students (UWES-9S) and a qualitative survey, we assessed three core dimensions of engagement: vigour, dedication, and absorption. A total of 82 undergraduate students (age range 19–27; 59% female, 41% male) participated in a semester-long comparative analysis using a pre-and-post intervention design. Sixty students from the Faculty of Science and Mathematics were assigned to the AI-assisted group due to logistical and course scheduling constraints, while twenty-two students from the Faculty of Metallurgy continued with traditional instruction, forming the control group. Our analysis employed a mixed ANOVA to explore interactions between time and instructional type, revealing significant improvements when the group switched to AI-assisted instruction for vigour ($F(1,80) = 22.35$, $p < 0.001$, $\eta p^2 = 0.218$), dedication ($F(1,80) = 24.48$, $p < 0.001$, $\eta p^2 = 0.234$), and absorption ($F(1,80) = 20.11$, $p < 0.001$, $\eta p^2 = 0.201$). Elevated Cohen's d values indicated large effect sizes, demonstrating both statistical and practical significance in these enhancements.

Keywords: UWES-9S, engagement, vigour, dedication, absorption, AI-assisted classroom

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INTRODUCTION

The role of AI in education

AI technologies have the potential to transform traditional teaching methods, offering innovative ways to enhance both teaching effectiveness and student learning experiences. For a comprehensive review of how AI may reshape higher education, see Zawacki-Richter et al. (2019). Similarly, Luckin (2018) highlights the potential of machine learning to personalise educational content, thereby improving student engagement. From personalised learning paths to automated assessments, AI applications are increasingly becoming integral components of modern education systems. ChatGPT, a conversational AI agent capable of personalised feedback and explanations, and Quizizz, a quiz-based platform with adaptive features, each introduce different AI-driven enhancements to the learning experience. ChatGPT, an AI-driven conversational agent, offers personalised tutoring and assistance, enabling interactive learning experiences that adapt to individual student needs. Quizizz, an AI-powered platform, uses gamified quizzes and real-time feedback to engage students and reinforce learning through an interactive and competitive format (Francis et al., 2025). These tools exemplify the broader movement towards incorporating adaptive learning platforms and automated feedback systems in education, aiming to elevate student engagement and improve educational outcomes.

The relationship between AI usage and student engagement

Despite the increasing integration of AI technologies, recent systematic reviews note a relative scarcity of studies that directly link the adoption of AI tools to concrete measures of student engagement, such as vigour, dedication, and absorption (Zawacki-Richter et al., 2019). Student engagement is a critical factor in academic success, encompassing the energy, enthusiasm, and immersion students exhibit in their learning processes. These dimensions are effectively measured by the Utrecht Work Engagement Scale for Students (UWES-9S), a tool originally developed to assess work engagement but aptly adapted for educational contexts. Understanding the relationship between AI usage and student engagement is essential for educators and policymakers aiming to enhance teaching strategies and integrate technology effectively. Although AI's potential to boost student motivation has been well-documented (Holmes et al., 2019), further empirical research is needed to clarify how AI-driven feedback and personalisation affect in-depth engagement over longer periods. There is a pressing need to investigate how AI-assisted classrooms, utilising tools like ChatGPT and Quizizz, influence these engagement dimensions compared to traditional learning environments.

Open research questions

Building upon the research gap identified in the previous section, this study aims to investigate the effects of AI-assisted learning environments on student engagement compared to traditional classroom settings. Earlier work (Luckin, 2018; Zawacki-Richter et al., 2019) has underscored the importance of establishing more precise links between AI functionalities and engagement outcomes, highlighting the need for targeted research. To achieve this goal, we have formulated specific research questions and hypotheses to guide our investigation.

RQ1: How does the use of AI-assisted learning tools affect the three dimensions of student engagement – vigour, dedication, and absorption – compared to traditional teaching methods?

RQ2: Which specific features of AI tools – such as personalisation, interactivity, and feedback mechanisms – most effectively enhance student engagement?

RQ3: Is there a significant correlation between increased student engagement facilitated by AI tools and improved academic performance?

Hypotheses

To address these research questions, we propose the following hypotheses:

H1: Students exposed to AI-assisted learning environments will exhibit statistically significantly higher levels of vigour, dedication and absorption compared to those in traditional classroom settings.

H2: Specific features of AI tools, such as personalisation, interactivity, and immediate feedback, have a significant positive impact on enhancing student engagement.

H3: There is a positive correlation between increased student engagement in AI-assisted learning environments and improved academic performance.

These hypotheses echo calls from prior studies (Holmes et al., 2019; Luckin, 2018) to more rigorously verify how AI-driven interventions can enrich students' learning experiences and performance metrics. By systematically evaluating these hypotheses, this study aims to provide empirical data that can inform educational stakeholders about the effectiveness of AI tools in enhancing student engagement. The outcomes are expected to contribute to curriculum development, teaching strategies, and technology integration, fostering improved educational practices and student learning experiences.

THEORETICAL FRAMEWORK AND LITERATURE REVIEW

The present study is grounded in the theoretical framework of work engagement as conceptualised by Schaufeli et al. (2006), which defines engagement through three core dimensions: vigour, dedication, and absorption. Originally developed to understand workplace engagement, this framework has been effectively adapted to educational settings, highlighting the universal nature of engagement across diverse types of work, including academic pursuits (Schaufeli et al., 2002). According to this group of authors, vigour, in the educational context, is characterised by elevated levels of energy and mental resilience during learning, where students exhibit persistence and effort in overcoming academic challenges. Dedication refers to the sense of significance, enthusiasm, inspiration, and pride that students feel towards their studies. Absorption denotes a state of deep immersion and concentration in academic activities, where students are fully engrossed in their tasks. To measure these core dimensions, our study employs the Utrecht Work Engagement Scale for Students (UWES-9S). It is a nine-item self-report instrument designed to measure these three dimensions of student engagement, with each dimension assessed by three items (Schaufeli et al., 2002; Schaufeli et al., 2006).

In recent years, the integration of Artificial Intelligence (AI) in education has been increasingly explored, with studies highlighting its potential to enhance student engagement and learning outcomes. AI technologies, such as adaptive learning platforms and intelligent tutoring systems, offer personalised learning experiences by adjusting content difficulty and providing immediate feedback based on individual student performance (Holmes et al., 2019). These features are designed to cater to diverse learning styles and needs, potentially increasing vigour by sustaining students' energy levels through appropriate challenges, fostering dedication by aligning learning activities with personal goals, and enhancing absorption by maintaining consistent engagement through interactive and immersive content (Ivanović, 2024). Despite the promising potential of AI in education, empirical research explicitly linking AI-assisted learning environments with the dimensions of student engagement as measured by the UWES-9S remains limited. Previous studies have primarily focused on the general benefits of AI technologies, such as improved academic performance and increased motivation (Chen et al., 2020) but have not extensively examined their impact on specific engagement dimensions. This gap underscores the need for research that integrates the theoretical framework of work engagement with the practical application of AI tools in educational settings. This study seeks to address this gap by applying Schaufeli et al.'s (2006) engagement theory to examine how specific features of AI-assisted learning tools impact student engagement.

RESEARCH DESIGN

This study employed a quasi-experimental mixed-methods research design to investigate the effects of AI-assisted learning environments on student engagement at the University of Montenegro.

Participants

The participant group comprised 82 second-year undergraduate students from the University of Montenegro. The intervention group consisted of 60 students from the Faculty of Science and Mathematics, while the control group included 22 students from the Faculty of Metallurgy. All participants had completed their first three semesters studying General English under the same traditional classroom settings (same teacher, course materials, class duration, etc.). Participants ranged in age from 19 to 27 years old, with an average age of 21.3 years (*SD* = 2.2). The sample included 48 females (59%) and 34 males (41%), reflecting a reasonable gender distribution representative of the university's student population within these faculties. All students were enrolled in programmes requiring similar levels of proficiency in General English, ensuring homogeneity in prior language exposure and learning experiences. The selection was based on convenience sampling due to logistical considerations, yet efforts were made to maintain diversity and control for potential biases.

Instruments

The primary instrument used in this study was the Utrecht Work Engagement Scale for Students (UWES-9S), a self-report questionnaire designed to measure student engagement across three dimensions: vigour, dedication, and absorption (Schaufeli et al., 2006). Studies across diverse cultural contexts have reported well-developed psychometric properties of the UWES-9S, consistently validating its three-factor structure and internal reliability. For instance, Carmona-Halty et al. (2021) found Cronbach's alpha values above 0.85 in their Chilean undergraduate sample, while Loscalzo & Giannini (2019) confirmed strong factorial validity in Italian university students. Similarly, Lovakov et al. (2017) reported satisfactory reliability and a clear three-dimensional structure in Russia, and comparable results were observed by Nerstad et al. (2010) in

Norway. These studies collectively reinforce the UWES-9S as a universal instrument capable of capturing the levels of student engagement globally. The UWES-9S comprises nine items, with three items dedicated to each engagement dimension. For the purpose of this study, our participants rated each item on a seven-point Likert scale ranging from 0 ("never") to 6 ("always/every day").

Sample items from the UWES-9S include "When I study, I feel like I am bursting with energy" for vigour, "I am enthusiastic about my studies" for dedication, and "I get carried away when I am studying" for absorption. In this study, the UWES-9S demonstrated high internal consistency, with Cronbach's alpha coefficients of 0.85 for vigour, 0.88 for dedication, 0.83 for absorption, and 0.90 for the overall scale. These reliability values align with the broader literature, where Cronbach's alphas for the UWES-9S typically range from 0.80 to 0.92 across various cultural contexts (Carmona-Halty et al., 2021; Loscalzo & Giannini, 2019; Lovakov et al., 2017; Nerstad et al., 2010; Petrović et al., 2017; Portalanza-Chavarria et al., 2017; Sánchez-Cardona et al., 2016; Tayama et al., 2019). Additionally, confirmatory factor analyses in these studies have consistently supported a three-factor structure – vigour, dedication, and absorption – reinforcing the scale's validity in measuring engagement. To complement the quantitative data, a supplementary survey with open-ended questions was administered to the intervention group. This survey aimed to gather detailed feedback on students' experiences with the AI-assisted learning environment. It focused on their perceptions of the effectiveness of AI tools, specific features that influenced their engagement, and suggestions for improvement. The qualitative data obtained provided deeper insights into the "why" and "how" behind the quantitative results, enriching the understanding of the impact of AI-assisted learning on student engagement.

Procedure

Participants were briefed about the study's purpose and procedures, ensuring transparency and informed consent. Ethical considerations were rigorously maintained throughout the study. All participants provided written informed consent after being informed about the study's aims, procedures, potential risks, and benefits. Data were anonymised to protect participant identity, with unique codes assigned to link pre- and post-intervention data without revealing personal information. Participants were assured that their involvement was voluntary and that they could withdraw from the study at any time without penalty.

The intervention involved integrating AI-assisted learning tools into the curriculum of the intervention group over a semester of approximately 15 weeks. The control group continued with traditional teaching methods during the same period, allowing for a comparative analysis of the two instructional approaches. In the AI-assisted learning environment, the study employed tools such as ChatGPT – an AI-driven conversational agent providing personalised tutoring and assistance, and Quizizz – an AI-powered platform offering gamified quizzes and real-time feedback. Classes were held twice a week, each lasting 90 minutes. Students actively used ChatGPT during class for interactive exercises (learning English through translation, grammar, reading, writing, etc.), problem-solving tasks and receiving immediate feedback. They also utilised ChatGPT for homework assignments, fostering continuous engagement beyond classroom hours. The teacher facilitated the use of AI tools by designing activities that required student interaction with ChatGPT and Quizizz. The teacher's role included monitoring progress, providing guidance, and using Quizizz to create competitive quizzes that reinforced learning objectives. Integration into the curriculum included personalised learning paths, with assignments that were tailored based on individual student performance (Accommodations). This approach allowed for differentiation and addressed specific learning needs. Interactive sessions were conducted using Quizizz, enhancing engagement through gamification and competition. Immediate feedback was provided by ChatGPT and Quizizz, enabling students to understand and correct mistakes promptly, thereby accelerating the learning process.

In contrast, the traditional learning environment employed in the control group consisted of teacher-centred instruction with a lower level of student interaction. Teaching methods included lectures and standard exercises and readings from prescribed textbooks without much technological enhancement. Technology use was limited to standard presentation tools such as PowerPoint, without the integration of AI applications. Student engagement activities focused on individual work and traditional assessments, such as written exams and essays, lacking the interactive and personalised elements present in the AI-assisted environment.

Data collection followed a structured procedure. In the pre-intervention phase during Week 1, all participants completed the UWES-9S to establish baseline engagement levels. Demographic data – including age, gender, and academic major – were collected to assess the sample's diversity and control for potential biases.

During the intervention period from Weeks 2 to 15, the intervention group engaged with AI tools during classes and for assignments, while the control group continued with traditional teaching methods. The consistent use of AI tools in the intervention group aimed to create a sustained impact on engagement levels, allowing for an assessment of changes over time. In the post-intervention phase in Week 16, all participants retook the UWES-9S to measure changes in engagement levels. The intervention group also completed the supplementary survey with open-ended questions, providing qualitative data on their experiences with the AI-assisted learning environment. Academic performance data, including exam scores and course grades, were collected for correlation analysis to explore the relationship between engagement levels and academic outcomes.

DATA ANALYSIS

The data analysis phase of the study was structured to evaluate the impact of AI-assisted versus traditional teaching methods on student engagement. Our initial analysis used descriptive statistics to summarise the baseline characteristics of the participants and their initial engagement levels. This step provided a clear understanding of the sample's composition and the starting state of engagement across both groups.

Descriptive results

Prior to conducting these analyses, we confirmed that the data met all the necessary assumptions for ANOVA (normality, homogeneity of variances, and sphericity for repeated measures), ensuring the validity of our results. Shapiro-Wilk tests confirmed normality, and Levene's tests verified homogeneity of variances.

Descriptive statistics were calculated to summarise the engagement levels of participants in both the AI-assisted and traditional teaching groups, measured before and after the intervention. The means and standard deviations for each dimension of the Utrecht Work Engagement Scale for Students (UWES-9S) – vigour, dedication, and absorption – are presented in Table 1.

➊ TABLE 1
Means and standard deviations of engagement scores pre- and post-intervention

Dimension	Group	Pre-intervention mean (*SD*)	Post-intervention mean (*SD*)
Vigour	AI-assisted	4.05 (1.20)	5.53 (1.10)
	Traditional	4.11 (1.30)	4.36 (1.20)
Dedication	AI-assisted	4.25 (1.10)	5.71 (1.00)
	Traditional	4.38 (1.20)	4.48 (1.10)
Absorption	AI-assisted	4.31 (1.30)	5.64 (1.20)
	Traditional	4.46 (1.20)	4.57 (1.30)

The AI-assisted group exhibited substantial increases in all three engagement dimensions post-intervention. In contrast, the traditional group showed only marginal improvements. These descriptive results suggest a positive impact of the AI-assisted learning environment on student engagement. Figure 1 presents a visual comparison of pre- and post-intervention engagement scores for both groups.

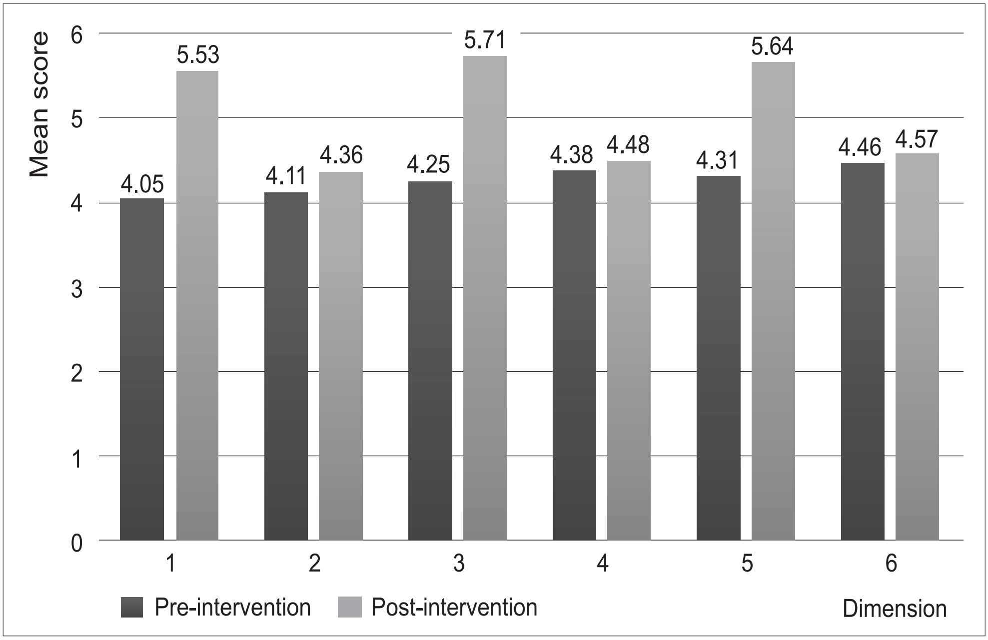


FIGURE 1
Pre- and post-intervention engagement scores comparison

In Figure 1, each dimension – Vigour, Dedication, Absorption – is represented by two bars: one for the AI-assisted group and one for the traditional group. These bars are labelled 1 through 6. Specifically, bars 1 (AI-assisted) and 2 (Traditional) show Vigour scores, bars 3 (AI-assisted) and 4 (Traditional) show Dedication scores, and bars 5 (AI-assisted) and 6 (Traditional) show Absorption scores. Within each bar, the darker portion indicates the Pre-intervention mean, while the lighter portion represents the Post-intervention mean, illustrating that the AI-assisted group experienced more substantial increases in all dimensions than the traditional group.

Correlation analysis

In addition to summarising engagement levels, we examined the associations between engagement and academic performance. Correlation analyses assessed both pre- and post-intervention engagement dimensions in relation to students' exam scores and overall course grades.

Pearson correlation coefficients were calculated to assess the relationships between engagement dimensions and academic performance (exam scores and course grades) post-intervention. Academic performance was measured via final exam scores and overall course grades. These objective evaluations were administered by an independent faculty member uninvolved in the intervention design.

➲ TABLE 2
Correlations between engagement dimensions and academic performance

Dimension	Correlation with academic performance (r)	p-value
Vigour	0.62	< 0.001
Dedication	0.68	< 0.001
Absorption	0.59	< 0.001

A strong positive correlation was found between dedication and academic performance ($r = 0.68$, $p < 0.001$), indicating that higher levels of dedication are associated with better academic outcomes. Vigour and absorption also showed significant positive correlations with academic performance. We further examined pre-intervention engagement correlations with academic performance, which were comparatively weaker (vigour: $r = 0.24$, $p = 0.03$; dedication: $r = 0.28$, $p = 0.01$; absorption: $r = 0.21$, $p = 0.05$), suggesting that the increase in engagement post-intervention may be a more reliable predictor of academic outcomes.

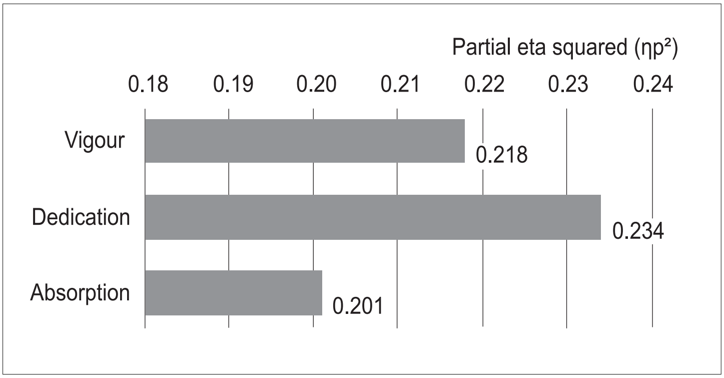
ANOVA results

As already mentioned, this study employed mixed Analysis of Variance (ANOVA) to evaluate the effects of instructional method (AI-assisted vs. traditional) and time (pre- and post-intervention) on student engagement dimensions. The interaction effects between instructional method and time were of primary interest.

➲ TABLE 3
ANOVA results and effect sizes for engagement dimensions

Dimension	F-value (1, 80)	p-value	Partial eta squared (ηp^2)	Effect size interpretation
Vigour	22.35	< 0.001	0.218	Large
Dedication	24.48	< 0.001	0.234	Large
Absorption	20.11	< 0.001	0.201	Large

The mixed ANOVA revealed significant interaction effects between instructional method and time for all three engagement dimensions. These large effect sizes indicate that a sizeable proportion of variance in engagement scores can be attributed to the interaction between instructional method and time. Figure 2 illustrates the partial eta squared values for the three engagement dimensions, reinforcing the quantitative analysis.



➲ FIGURE 2
Effect sizes by dimension

The bars represent the partial eta squared (ηp^2) for each engagement dimension, highlighting the strong influence of the AI-assisted intervention on vigour, dedication, and absorption.

This statistical narrative is further supported by the application of Tukey's Honestly Significant Difference (HSD) post-hoc tests. Following the detection of significant differences by the mixed ANOVA, Tukey's HSD was employed to confirm which specific pairwise comparisons are statistically significant while controlling for type I errors across multiple tests. This method corroborated the large effect sizes observed, affirming the uplift in engagement within the AI-assisted group, with all dimensions yielding p-values less than 0.001.

To further quantify the magnitude of the differences observed between the AI-assisted and traditional teaching groups, Cohen's d was calculated for each engagement dimension. Cohen's d is a measure of effect size that expresses the difference between two means in terms of standard deviation units, allowing for the assessment of practical significance alongside statistical significance (Cohen, 1988). According to Cohen's (1988) benchmarks, effect sizes of 0.2 are considered small, 0.5 medium, and 0.8 or above large. The calculated effect sizes exceeding 1.0 for all three engagement dimensions indicate that the differences are not only statistically significant but also of considerable practical importance.

The effect sizes for the changes in engagement dimensions are as follows:

Vigour: The AI-assisted group exhibited a large effect size with Cohen's $d = 1.29$, indicating a substantial increase in vigour compared to the traditional group.

Dedication: A large effect size was also observed for dedication, with Cohen's $d = 1.39$, suggesting a significant enhancement in students' dedication within the AI-assisted learning environment.

Absorption: The effect size for absorption was large as well, with Cohen's $d = 1.06$, reflecting a notable improvement in the level of absorption among students using AI-assisted tools.

These substantial effect sizes corroborate the results of the mixed ANOVA, emphasising the meaningful impact of AI-assisted learning environments on enhancing student engagement across vigour, dedication, and absorption.

THEMATIC ANALYSIS

To gain a more profound insight into how AI-assisted learning environments affect student engagement, additional qualitative data were collected beyond the quantitative measures provided by the Utrecht Work Engagement Scale for Students (UWES-9S). Recognising the need for a broader dataset, a supplementary survey composed of open-ended questions was administered to the intervention group at the end of the semester. This approach was intended to gather data about the students' firsthand experiences and insights into the specific features of AI tools and their influence on the engagement aspects of vigour, dedication, and absorption. All 60 students in the intervention group participated in the qualitative survey, ensuring consistency between the quantitative and qualitative datasets. These students had also completed the UWES-9S, allowing for a comprehensive analysis of their engagement levels. The open-ended questions invited students to reflect on their experiences with the AI-assisted learning environment, focusing on aspects such as personalisation, interactivity, immediate feedback, and any other features they found impactful. The thematic analysis began with an exhaustive review of the narrative responses collected from these students. Responses were initially coded based on the descriptions of student experiences, particularly emphasising their perceptions of personalisation, interactivity, and real-time feedback. The coding process involved identifying meaningful patterns or phrases that succinctly captured the students' sentiments. As the analysis progressed, codes were aggregated into broader themes using a constant comparative method to refine and define these themes until saturation was reached. Saturation was considered achieved when additional data no longer introduced new insights or themes, ensuring that the analysis comprehensively represented the students' experiences. Two independent researchers coded the responses, achieving an inter-rater reliability (Cohen's κ) above 0.80, ensuring the trustworthiness of the thematic analysis.

Six main themes emerged from the data, each encapsulating distinct aspects of student engagement driven by AI features:

1. *Enhanced personal engagement (35.6%)*: This theme captures how personalised interactions with AI tools, especially ChatGPT, fostered a deeper connection between students and the learn-

ing material. Students frequently noted that customising content to their learning needs made the material more accessible and relatable, thereby enhancing their intrinsic motivation.

2. *Motivation through competition (32.2%)*: Many responses highlighted the motivational boost provided by the competitive elements of AI tools within Quizizz. Students appreciated the gamified aspects, which transformed learning into a dynamic and enjoyable challenge. This competitive spirit was particularly noted to increase students' dedication to mastering the content.

3. *Accelerated learning curve (16.7%)*: The immediate feedback provided by AI tools was repeatedly mentioned as a critical factor in enhancing the absorption aspect of engagement. Students valued the ability to receive instant feedback, enabling them to quickly understand and rectify mistakes, thereby maintaining a prominent level of focus and effectively speeding up the learning process.

4. *Collaborative learning enhancements (7.7%)*: Apart from competition, AI tools facilitated greater collaboration among students through shared quizzes or projects, fostering a community learning environment and enhancing communication and teamwork among peers. Interestingly (cf. Theme no. 2), the data revealed that more students attributed greater value to competitive elements than to collaborative aspects in their learning environments. This preference underscores a distinctive inclination towards competitive engagement strategies, which may stimulate motivation and drive academic performance more effectively than cooperative methods.

5. *Emotional engagement (3.9%)*: This theme revolves around how AI tools affected the emotional aspects of student engagement, such as reducing anxiety associated with assessments or increasing confidence through progressive learning modules. Emotional engagement is crucial for motivation and long-term educational success.

6. *Technological literacy skills (3.9%)*: Emphasising the role of AI tools in enhancing students' technological skills, this theme covers how frequent interaction with these tools helped students become more proficient with digital technologies, an essential skill in today's tech-driven world.

To explore the relationship between the qualitative themes and the quantitative engagement dimensions measured by the UWES-9S, we quantified the presence of themes in individual students' responses. Each student's response was coded for the presence (1) or absence (0) of each theme. This process resulted in a dataset where each student had both quantitative engagement scores and binary indicators for each qualitative theme. Point-biserial correlation analysis to examine the associations between the presence of each theme and the corresponding engagement dimension scores was then conducted. Each student's qualitative response was binary-coded for theme presence to quantify relationships. Although such an approach reduces thematic richness, it allows preliminary statistical linkage between engagement scores and emergent qualitative patterns. We acknowledge this as an exploratory step. The point-biserial correlation is appropriate when one variable is dichotomous (presence or absence of a theme), and the other is continuous (engagement scores). We focused on post-intervention UWES-9S scores here, reflecting engagement after exposure to AI activities. However, to address potential changes from baseline, we also calculated correlations with pre-intervention engagement scores, which yielded weaker and non-significant relationships (r_{pb} range = 0.10–0.15, $p > 0.05$). This suggests that the themes identified in the qualitative data aligned more closely with the higher engagement levels reported after students experienced AI-assisted learning.

The results revealed significant correlations between the three most prominent themes and engagement dimensions (Table 4):

Enhanced personal engagement and Vigour: A significant positive correlation was found between the presence of the enhanced personal engagement theme and vigour scores ($r_{pb} = 0.43$, $p < 0.001$). This suggests that students who reported enhanced personal engagement tended to have higher levels of energy and mental resilience in their studies.

Motivation through competition and Dedication: There was a significant positive correlation between the motivation through competition theme and dedication scores ($r_{pb} = 0.46$, $p < 0.001$). This indicates that students who highlighted competitive elements as motivating factors exhibited greater enthusiasm and commitment to their studies.

Accelerated learning curve and Absorption: The presence of the accelerated learning curve theme was significantly correlated with absorption scores ($r_{pb} = 0.40$, $p < 0.01$), suggesting that students who valued immediate feedback and accelerated learning experienced deeper immersion in their academic tasks.

TABLE 4
Point-biserial correlations between themes and engagement dimensions

Theme	Engagement	Dimension correlation coefficient (r_{pb})	p-value
Enhanced personal engagement	Vigour	0.43	<0.001
Motivation through competition	Dedication	0.46	<0.001
Accelerated learning curve	Absorption	0.40	<0.01

These statistical correlations provide empirical support for the connections between the qualitative themes and the quantitative engagement dimensions. The findings indicate that specific features of AI-assisted learning tools are associated with higher levels of student engagement as measured by the UWES-9S.

These insights are invaluable for educational technology developers and educators seeking to optimise AI tools to foster more engaging and effective learning environments. The integration of quantitative and qualitative data provides a comprehensive understanding of how AI features such as personalisation, competition, and immediate feedback contribute to enhancing vigour, dedication, and absorption among students.

DISCUSSION OF THE RESULTS

The present study investigated the impact of AI-assisted learning environments on student engagement among undergraduate students at the University of Montenegro, using the Utrecht Work Engagement Scale for Students (UWES-9S) to measure the dimensions of vigour, dedication, and absorption. The findings indicate that students exposed to AI-assisted instructional methods showed significant improvements in all three dimensions of engagement compared to those in traditional teaching settings. Specifically, the AI-assisted group demonstrated substantial increases in vigour, dedication, and absorption scores post-intervention, with large effect sizes observed. Furthermore, a strong positive correlation was found between increased dedication and academic performance, suggesting that heightened engagement is associated with better educational outcomes. These results align with Schaufeli et al.'s (2006) work engagement theory, which posits that engagement is characterised by elevated levels of energy, enthusiasm, and immersion in activities. The significant improvements in the engagement dimensions suggest that AI-assisted learning environments effectively enhance these aspects of student experience. The findings also corroborate previous research indicating that personalised and interactive learning tools can boost student motivation and engagement (Chen et al., 2020; Holmes et al., 2019). The increase in vigour observed in the AI-assisted group suggests that the stimulating and responsive nature of AI tools can effectively boost students' energy and resilience in academic settings. This is consistent with previous studies highlighting the role of adaptive learning technologies in sustaining student motivation by providing appropriate challenges (Ward et al., 2024). The AI tools used in this study, ChatGPT and Quizizz, have contributed to sustaining high energy levels by offering immediate feedback and interactive learning experiences.

The marked improvement in dedication highlights AI's capacity to make learning more relevant and personally meaningful to students through customised feedback and adaptive learning paths. This personalisation helps students see the value and importance of their studies, increasing their emotional and cognitive investment in their education. Similar findings have been reported by Kizilcec et al. (2017), who found that personalised feedback in online learning environments enhances student commitment and course completion rates. The significant rise in absorption scores indicates that AI-enhanced tools are particularly effective at capturing and sustaining students' attention, likely due to their interactive and immersive nature. This finding supports the notion that engaging content delivery methods, facilitated by AI technologies, can promote deep learning and sustained focus (Johnson & Lester, 2016). The interactive features of AI tools may create a flow-like experience, where students become fully immersed in the learning activity (Csikszentmihalyi, 1990). The positive correlation between increased engagement, particularly dedication, and improved academic performance reinforces the importance of fostering engagement to enhance educational outcomes. This relationship echoes the findings of Carmona-Halty et al. (2021), who demonstrated that academic engagement mediates the relationship between positive emotions and academic performance.

Our study extends the application of Schaufeli et al.'s (2006) work engagement theory to the context of AI-assisted learning environments. The observed enhancements in vigour, dedication, and absorption align with the theoretical underpinnings that emphasise the importance of energy, enthusiasm, and immersion in promoting engagement. By demonstrating that AI tools can effectively enhance these dimensions, the study provides empirical support for integrating technological advancements with established psychological frameworks. Previous research has highlighted the potential of AI in education to personalise learning experiences and improve engagement (Chen et al., 2020; Holmes et al., 2019). For instance, Chen et al. (2020) reviewed AI applications in education and found that adaptive learning systems that tailor content to individual needs can significantly enhance student motivation and learning outcomes. Our findings corroborate these conclusions, showing that AI-assisted environments contribute to higher engagement levels compared to traditional methods.

The findings have significant implications for educational practices and policy development. The enhanced vigour suggests that incorporating AI elements that actively engage students can reduce feelings of fatigue and disinterest. Educational policymakers might consider integrating AI techno-logies that simulate real-world problems and interactive scenarios to maintain high energy levels in educational environments (Holmes et al., 2019). The improvement in dedication underscores the value of personalised learning experiences. Institutions may leverage this insight by adopting AI systems that provide tailored educational content, fostering deeper emotional connections with the academic material and promoting a sense of ownership over learning achievements (Kizilcec et al., 2017). The rise in absorption scores indicates that AI-enhanced tools effectively capture and sustain student attention. This suggests a shift towards educational strategies that emphasise engaging content delivery capable of holding student interest over extended periods. Policymakers could advocate for the development and integration of AI tools that present information in an inherently engaging and captivating manner, ensuring active participation in the learning process (Johnson & Lester, 2016).

Limitations

Despite the promising results, several limitations must be acknowledged. First, the study relied on self-report measures using the UWES-9S, which may introduce response biases such as social desirability or inaccurate self-assessment (Podsakoff et al., 2003). Future research should consider incorporating objective measures of engagement, such as behavioural analytics from AI platforms or observational assessments, to complement self-reported data. Second, the quasi-experimental design without random assignment limits the ability to establish causality. Participants were assigned to groups based on faculty affiliation, which may have introduced selection biases. Differences in academic culture or student characteristics between faculties could confound the results. Randomised controlled trials would strengthen the causal inferences and control for potential confounding variables. Third, the sample size, particularly for the control group (n = 22), was relatively small. This may affect the generalisability of the findings to broader populations. Larger sample sizes and replication across different institutions and disciplines are needed to validate and extend the conclusions. Additionally, the study was conducted over a single semester, providing a snapshot of the effects of AI-assisted learning. Longitudinal studies examining the long-term impact on engagement and academic performance would offer insights into the sustainability of the benefits observed.

Recommendations for future research

Future research should aim to expand on these findings by exploring the longitudinal impacts of AI engagement and examining which specific AI features are most effective across different student demographics. Investigating the role of factors such as cultural context, subject matter, and individual differences in receptivity to AI-assisted learning can provide a better understanding of how to optimise these technologies for diverse learner populations. Moreover, future research should address the potential challenges and ethical considerations associated with AI in education, such as data privacy, algorithmic bias, and the digital divide between students exposed to AI-assisted learning environments and those receiving traditional instruction. Ensuring equitable access to AI technologies is crucial to avoid exacerbating existing educational inequalities.

CONCLUSIONS

This study aimed to investigate the impact of AI-assisted learning environments on student engagement, specifically focusing on the dimensions of vigour, dedication, and absorption as measured by the Utrecht Work Engagement Scale for Students (UWES-9S). Additionally, the research sought to explore the relationship between enhanced engagement and academic performance and to identify specific AI features that most effectively enhance student engagement. The findings conclusively demonstrate that integrating AI-assisted tools within the educational context significantly enhances student engagement across all measured dimensions. The AI-assisted group exhibited substantial improvements in vigour, dedication, and absorption, with large effect sizes observed in the mixed ANOVA analysis. Dedication showed a strong positive correlation with academic performance, underscoring the potential of increased engagement to contribute to better learning outcomes. These preliminary results provide empirical support for the transformative potential of AI in education. The dynamic and interactive nature of AI tools resonates more effectively with students than traditional teaching methods, leading to deeper involvement and commitment to their studies. Features such as personalised feedback, immediate response mechanisms, and interactive learning experiences offered by AI tools like ChatGPT and Quizizz not only boost engagement levels but also facilitate improved academic performance.

The practical implications of these findings are significant for educators and administrators. Educational institutions should consider integrating AI-assisted methodologies into their curricula to enhance student engagement and academic outcomes. By incorporating AI tools that offer personalised and interactive learning experiences, educators can cater to diverse learning needs, maintain high energy levels in the classroom, and foster a deeper emotional connection between students and their studies. Training programmes for educators should include components on effectively utilising AI tools to enhance teaching strategies. Professional development initiatives can equip teachers with the skills necessary to integrate AI technologies into their instructional practices, ensuring they can leverage these tools to maximise student engagement.

At the policy level, the findings highlight the need for educational frameworks that support the integration of AI technologies. Policymakers should advocate for the development and implementation of AI tools that enhance engagement and learning outcomes. This includes allocating resources for technological infrastructure, supporting research and development of educational AI applications, and establishing guidelines for effective and ethical use of AI in classrooms. The social relevance of this study is profound, as it addresses the growing demand for educational practices that prepare students for a technologically advanced society. By fostering higher levels of engagement and improving academic performance, AI-assisted learning environments contribute to the development of a skilled and knowledgeable workforce. This has far-reaching implications for economic growth, innovation, and societal advancement.

REFERENCES

Carmona-Halty, M., Salanova, M., Llorens, S., & Schaufeli, W. B. (2021). Linking positive emotions and academic performance: The mediated role of academic psychological capital and academic engagement. *Current Psychology, 40*(6), 2938–2947. https://doi.org/10.1007/s12144-019-00227-8

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

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed.). Lawrence Erlbaum Associates.

Csikszentmihalyi, M. (1990). *Flow: The psychology of optimal experience.* Harper & Row.

Francis, N. J., Jones, S., & Smith, D. P. (2025). Generative AI in higher education: Balancing innovation and integrity. *British Journal of Biomedical Science, 81,* 14048. https://doi.org/10.3389/bjbs.2024.14048

Holmes, W., Bialik, M., & Fadel, C. (2019). *Artificial intelligence in education: Promises and implications for teaching and learning*. Center for Curriculum Redesign.

Ivanović, I. (2024). Game-based learning and underachieving students: Replacing the traditional paradigm in Montenegro? *Education and Information Technologies, 29*, 21965–21993. https://doi.org/10.1007/s10639-024-12740-w

Johnson, W. L., & Lester, J. C. (2016). Face-to-face interaction with pedagogical agents, twenty years later. *International Journal of Artificial Intelligence in Education, 28*(4), 543–557. https://doi.org/10.1007/s40593-018-0171-9

Kizilcec, R. F., Pérez-Sanagustín, M., & Maldonado, J. J. (2017). Self-regulated learning strategies predict learner behavior and goal attainment in massive open online courses. *Computers & Education, 104,* 18–33. https://doi.org/10.1016/j.compedu.2016.10.001

Loscalzo, Y., & Giannini, M. (2019). Study engagement in Italian university students: A confirmatory factor analysis of the Utrecht Work Engagement Scale–Student version. *Social Indicators Research, 142*, 845–854. https://doi.org/10.1007/s11205-018-1943-y

Lovakov, A. V., Agadullina, E. R., & Schaufeli, W. B. (2017). Psychometric properties of the Russian version of the Utrecht Work Engagement Scale (UWES–9). *Psychology in Russia: State of the Art, 10*(1), 145–162. https://doi.org/10.11621/pir.2017.0111

Luckin, R. (2018). *Machine learning and human intelligence: The future of education for the 21st century*. UCL IOE Press.

Nerstad, C. G. L., Richardsen, A. M., & Martinussen, M. (2010). Factorial validity of the Utrecht Work Engagement Scale (UWES) across occupational groups in Norway. *Scandinavian Journal of Psychology, 51*(4), 326–333. https://doi.org/10.1111/j.1467-9450.2009.00770.x

Petrović, I. B., Vukelić, M., & Čizmić, S. (2017). Work engagement in Serbia: Psychometric properties of the Serbian version of the Utrecht Work Engagement Scale (UWES). *Frontiers in Psychology, 8,* 1799. https://doi.org/10.3389/fpsyg.2017.01799

Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology, 88*(5), 879–903. https://doi.org/10.1037/0021-9010.88.5.879

Portalanza-Chavarria, C. A., Grueso-Hinestroza, M. P., & Duque-Oliva, E. J. (2017). Properties of the Utrecht Work Engagement Scale (UWES–S9): Exploratory analysis of students in Ecuador. *Innovar, 27*(64), 145–156. https://doi.org/10.15446/innovar.v27n64.62374

Sánchez-Cardona, I., Rodríguez-Montalbán, R., Toro-Alfonso, J., & Moreno, I. (2016). Psychometric properties of the Utrecht Work Engagement Scale–Student (UWES–S) in university students in Puerto Rico. *Revista Mexicana de Psicología, 33*(2), 121–134.

Schaufeli, W. B., Bakker, A. B., & Salanova, M. (2006). The measurement of work engagement with a short questionnaire: A cross–national study. *Educational and Psychological Measurement, 66*(4), 701–716. https://doi.org/10.1177/0013164405282471

Schaufeli, W. B., Martinez, I. M., Marques-Pinto, A., Salanova, M., & Bakker, A. (2002). Burnout and engagement in university students: A cross-national study. *Journal of Cross-Cultural Psychology, 33*(5), 464–481. https://doi.org/10.1177/0022022102033005003

Tayama, J., Schaufeli, W., Shimazu, A., Tanaka, M., & Takahama, A. (2019). Validation of a Japanese version of the Work Engagement Scale for Students. *Japanese Psychological Research, 61*(4), 262–272. https://doi.org/10.1111/jpr.12229

Ward, B., Bhati, D., Neha, F., & Guercio, A. (2025). Analyzing the impact of AI tools on student study habits and academic performance. In *2025 IEEE 15th Annual Computing and Communication Workshop and Conference* (CCWC) (pp. 434–440). IEEE. https://doi.org/10.1109/CCWC62904.2025.10903692

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,* Article 39. https://doi.org/10.1186/s41239-019-0171-0

Usporedna analiza angažiranosti studenata u tradicionalnoj nastavi i nastavi potpomognutoj umjetnom inteligencijom primjenom UWES-9S

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U ovom istraživanju empirijski ispitujemo utjecaj obrazovnog okruženja podržanog umjetnom inteligencijom u odnosu na tradicionalne nastavne metode na angažiranost studenata na Sveučilištu Crne Gore. Koristeći se Utrechtskom ljestvicom angažiranosti studenata (UWES-9S) te kvalitativnim upitnikom procijenili smo tri temeljne dimenzije angažiranosti: energičnost, predanost i zadubljenost. Ukupno 82 studenta preddiplomskoga studija (dob od 19 do 27 godina; 59 % studentica, 41 % studenata) sudjelovalo je u usporednoj analizi tijekom jednoga semestra, uz mjerenje rezultata prije i nakon intervencije. Zbog logističkih razloga i rasporeda nastave, šezdeset studenata s Prirodoslovno-matematičkoga fakulteta raspoređeno je u skupinu s nastavom podržanom umjetnom inteligencijom, dok su dvadeset i dva studenta s Metalurškoga fakulteta nastavili s tradicionalnim oblikom nastave, čineći kontrolnu skupinu. Analiza je provedena primjenom mješovitog ANOVA testa za istraživanje interakcija između vremena i vrste nastave, pri čemu su zabilježena značajna poboljšanja nakon prelaska na nastavu uz podršku umjetne inteligencije za energičnost ($F(1,80) = 22{,}35$, $p < 0{,}001$, $\eta p^2 = 0{,}218$), predanost ($F(1,80) = 24{,}48$, $p < 0{,}001$, $\eta p^2 = 0{,}234$) i zadubljenost ($F(1,80) = 20{,}11$, $p < 0{,}001$, $\eta p^2 = 0{,}201$). Povišene vrijednosti Cohenova indeksa d upućuju na velike veličine efekta, što potvrđuje statističku i praktičnu važnost ovih poboljšanja.

Ključne riječi: UWES-9S, angažiranost, energičnost, predanost, zadubljenost, učionica potpomognuta umjetnom inteligencijom