Exploring AI-Assisted Teacher Support Mechanism for University Students' Learning Engagement

Fengjun Qi and Xianyin Li
Krirk University, Bangkok, Thailand
Corresponding Author, E-mail: 6319111@student.krirk.ac.th

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Abstracts

The application of artificial intelligence in the field of education has been expanding rapidly. AI-assisted systems can provide educators with enhanced teaching support and resources, leading to increased attention on the relationship between teacher support and student learning engagement. Academic research indicates that student learning engagement serves as a crucial indicator for evaluating educational quality, exerting positive effects on academic performance and personal development. Therefore, exploring the underlying principles and external conditions that foster student learning engagement becomes paramount. Student learning engagement represents a dynamic state, influenced by the support provided by educators within the learning environment. Despite the acknowledged significance of teacher support, the existing literature still lacks an in-depth understanding of the mechanisms through which teacher support impacts learning engagement. Hence, this study approaches the subject from the perspective of AI-assisted systems, aiming to investigate the influence of teacher support on university students' learning engagement.

Keywords: Artificial Intelligence; Teacher Support; Learning Engagement; Academic Research

Introduction

The exponential growth of artificial intelligence (AI) is revolutionising several sectors, encompassing the realm of education. The use of artificial intelligence (AI) into educational systems has the potential to improve the calibre of instruction and educational achievements by offering tailored and individualised assistance. Nevertheless, the current state of study regarding the implementation of artificial intelligence (AI) in the field of education is still in its developmental stages. Although previous research has recognised the significance of teacher assistance in fostering student engagement, there is still a dearth of comprehensive comprehension about the specific pathways through which AI-assisted teacher support influences engagement.

The primary objective of this study is to fill the existing research gap by examining the impact of AI-assisted teacher support on the learning engagement of university students. This study examines the possible moderating aspects of academic self-efficacy and learning styles in relation to the topic at hand. Student engagement is a cognitive phenomenon characterised by the exertion of mental and physical effort, the presence of genuine interest, and active participation in educational endeavours. It functions as a pivotal determinant of educational excellence, exhibiting favourable outcomes on academic achievement and personal growth.

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Hence, investigating the impact of AI-assisted teacher assistance on student engagement emerges as a significant avenue for scholarly inquiry. The present study presents a conceptual framework that aims to integrate self-efficacy theory, flow theory, and learning style theory in order to investigate the underlying dynamics. The hypothesis posits that:

- AI-assisted teacher support positively impacts student learning engagement.
- This impact will vary based on students' academic self-efficacy.
- This impact will vary based on students' learning styles.

The research methodology employed in this study would involve a mixed-methods approach, utilising surveys and interviews as data collection tools, in order to empirically examine and evaluate the proposed hypotheses. The objective of the research is to offer valuable insights on how to optimise artificial intelligence technologies in order to improve student experiences and outcomes. The present study aims to enhance the theoretical comprehension of the intricate relationship among AI support systems, individual variances, and engagement.

Literature Review

The integration of artificial intelligence (AI) within the educational landscape has become an increasingly prominent and captivating field of inquiry (Luckin et al., 2016; Woolf et al., 2013). The use of intelligent tutoring systems, adaptive learning platforms, and AI-driven classroom assistants has demonstrated potential benefits in the arena of teaching and learning (du Boulay, 2016; Rus et al., 2013). These advancements have been made possible by recent technological advances. These technology advancements have the ability to completely change the way that educational procedures are carried out. However, it is essential to recognise that despite the progress that has been achieved, the field of study pertaining to the use of AI in education is still developing and is still in its early stages (Holmes et al., 2019). This is something that must be acknowledged.

Teacher support is a fundamental cornerstone of an effective education. It encompasses a variety of characteristics such as care, attentive listening, encouragement, respect, and guidance provided by educators to foster student learning and holistic development (Brewster & Bowen, 2004; Ouyang, 2005; Trickett & Moos 1973). These characteristics are provided by educators to foster student learning and holistic development (Brewster & Bowen, 2004; Ouyang, 2005). This support manifests itself in a variety of guises, including aid with knowledge-based, emotional, and social interactions, which is especially important in the context of online learning settings (Jiang, 2018). There is no question that having assistance from teachers acts as a driving force in elevating the academic engagement, motivation, and overall accomplishment of students (Chen, 2005; Lam et al., 2014; Wang, 2018). Despite the fact that the good influence has been recognised by a large number of people, there is still a need for a deeper comprehension of the underlying processes that are responsible for its efficacy. According to Christenson et al. (2012), Finn (1989), and Lam et al. (2014), student involvement may be defined as a commitment of attention, interest, effort, and energy towards learning activities. Student engagement is an essential factor in determining learning outcomes. Engaged students exhibit characteristics such as active involvement, delight in their work, and focused effort (Lam et al., 2014; Quin, 2017; Wellborn, 1991). Engagement serves as a mediator between the affects of their surroundings and their educational accomplishments.

Student engagement is a complex relationship between students and the academic work that they are attempting to do (Johnson & Sinatra, 2013; Martin, 2018). This relationship is grounded in a psychological process that lives on motivation and task interaction.

Self-efficacy beliefs, which are a foundational component of motivational psychology (Bandura, 1977; Schunk & DiBenedetto, 2020), have been shown to have a significant impact on a person's level of motivation, resiliency, and academic achievements. Students that are equipped with strong academic self-efficacy have greater levels of confidence in their ability to overcome academic problems. (Heutte et al., 2016; Nakamura & Csikszentmihalyi, 2014) The Flow theory is another significant approach that postulates that optimum engagement occurs when the alignment of challenges and skills is harmonious. This theory was developed by Csikszentmihalyi and Nakamura. The process of meaning building via the use of experiential learning is given a lot of weight in the constructivist school of thought (Driscoll, 2000; Ultanir, 2012), as mentioned before. On the other hand, social development theory emphasises the central role that social contact plays in cognitive development (Scott & Palincsar, 2013; Vygotsky, 1980; Scott & Palincsar, 2013). These conceptual frameworks, taken as a whole, provide insight on the possible moderating impact of individual variations in the process of forming the consequences of AI assistance.

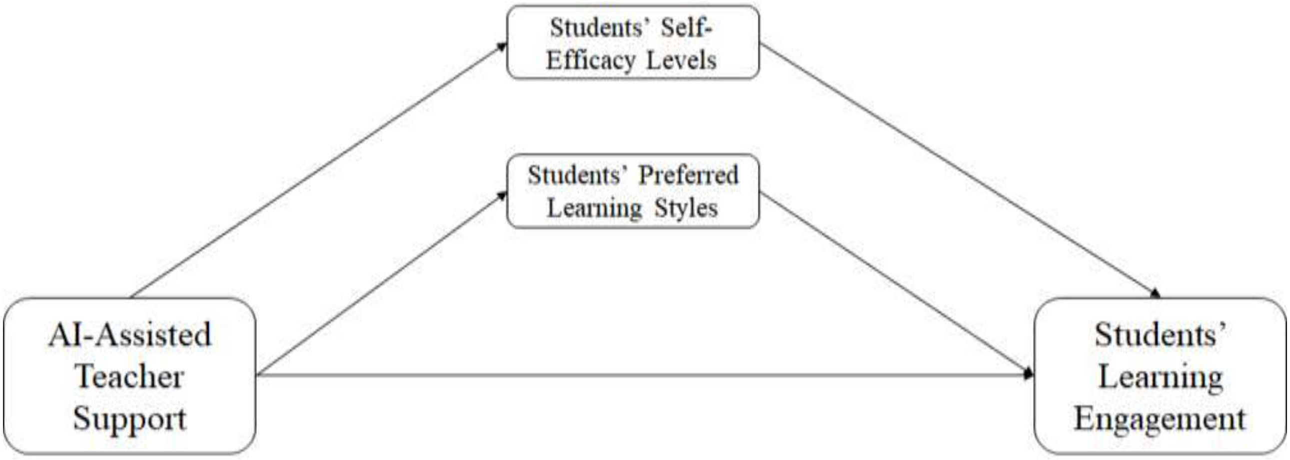
The advent of empirical research has started to shed light on the influence that AI has had on the educational system. Intelligent tutoring systems and adaptable platforms have exhibited promising benefits, including greater learning and increased engagement (Koedinger et al., 1997; Liu et al., 2020; Suzgun Kantarci, 2021). It has also been shown that there is a dynamic interaction taking place between the learning styles of students and the efficiency of adaptive systems (Akbulut & Cardak, 2012; Graf et al., 2009). Despite this, there is still a vast area of research that has not been done, and there is a pressing need for more investigation into the complex factors that impact university students' involvement with AI-supported teacher help across a wide variety of individual characteristics. The current investigation aims to fill this significant gap in the previously published research.

Research Method

Research Framework and Assumptions

The conceptual framework of this study incorporates three prominent ideas in order to provide insight into the correlation between AI-assisted teacher assistance and student participation in the learning process.

Fig. 1: Conceptual Framework



The Self-Efficacy Theory, as conceptualised by Bandura, asserts that an individual's self-efficacy, which refers to their belief in their own capabilities, plays a pivotal role in shaping their motivation, level of effort, and ability to persevere in the face of obstacles. Students who possess a higher level of academic self-efficacy have greater confidence in their ability to acquire knowledge and achieve success. According to self-efficacy theory, it may be inferred that the provision of AI support will have a greater influence on student engagement for those who possess higher levels of self-efficacy.

According to Csikszentmihalyi's flow theory, the state of optimal engagement is achieved when there is a congruence between the demands presented by an activity and an individual's talents and level of interest. Individual learners possess distinct learning preferences that impact their ability to effectively engage with and overcome challenges. Therefore, according to flow theory, the extent to which AI help influences engagement will be contingent upon its compatibility with students' individual learning styles.

The Social Development Theory, proposed by Vygotsky, underscores the significance of social contact in facilitating cognitive development. The provision of teacher advice and assistance plays a crucial role in facilitating the development of students' knowledge and abilities. This approach emphasises the crucial significance of AI-assisted teacher assistance in facilitating student engagement.

Based on the integration of these three theories, this study proposes three main hypotheses:

H1: AI-assisted teacher support has a significant positive impact on students' learning engagement.

H2: The impact of AI-assisted teacher support on learning engagement will vary based on students' academic self-efficacy levels.

H3: The impact of AI-assisted teacher support on learning engagement will vary based on students' preferred learning styles.

Formulation of the Survey

A well-structured questionnaire will be painstakingly constructed in order to methodically collect comprehensive data for the purpose of this investigation. The participant's perspectives, experiences, and features in relation to AI-assisted teacher assistance, learning engagement, academic self-efficacy, learning styles, and demographics will be elicited through the use of carefully prepared items that will be included in the questionnaire.

3.2.1 The Perceived Level of Support That Artificial Intelligence Can Offer Teachers

Participants are going to be asked to rate how much help they feel they receive from AI-assisted teachers. Items will query as to the amount to which AI tools have offered them with meaningful feedback, guidance, resources, and help over the entirety of their educational career. The purpose of this section is to collect the participants' subjective evaluations on the efficiency and influence of AI help on their respective educational experiences.

3.2.2 Participation in Education

The participants' cognitive, emotional, and behavioral participation in the educational activities they are participating in will be investigated using a series of items that will be constructed so that the level of learning engagement may be evaluated. Participants will be asked to evaluate their degree of immersion, interest, and involvement in learning activities that are supported by AI-assisted teachers.

3.2.3 Effectiveness of Oneself in Academics

The participants' academic self-efficacy will be evaluated through the use of a questionnaire that contains items designed to test participants' perceptions regarding their academic capabilities. These items will enquire about the participants' level of confidence in their ability to tackle academic problems, manage their studies, and accomplish their learning goals while receiving assistance from AI.

3.2.4 Styles of Education

On the basis of Kolb's Learning Style Inventory, participants will be led through questions and activities that are designed to represent their preferred learning styles. Participants will be placed into separate learning style groups based on their responses to these questions, which will allow the study to investigate possible variances in the influence of AI-assisted assistance on engagement across a variety of learning preferences.

3.2.5 A look at the demographics

The participants are going to be asked for their demographic information so that the analysis can have some context for what is going on. These may include the academic year, topic of study, gender, age, and whether or not the individual has had any previous exposure or experience with AI-assisted learning systems. The findings will be easier to interpret in connection to the various participant profiles if these demographic data points are included.

3.2.6 Validation by Utilizing Previously Conducted Research Scales

In order to guarantee the dependability and validity of the data that are gathered, established scales that have been utilized in previous research will be modified and incorporated into the questionnaire. These scales have been subjected to stringent validation methods in prior research and are acknowledged in the academic community. The design of the questionnaire ensures that a high quality of measurement is maintained at all times by making use of these validated scales.

Data collection

Data collection for this project will begin with the recruitment of a varied and representative sample of university students. Participation will be invited via university email lists, internet platforms, and relevant social media groups. Participants will get a secure online questionnaire link before engagement. This questionnaire will lead participants through well-structured sections on different study topics. Ethical concerns will guide data collecting. A detailed informed consent statement will explain the study's goals, methods, risks, rewards, and the freedom to withdraw at any time without penalty. Data gathering will not include personal identifiable information to protect participants' privacy.

Data Analysis

Research Framework and Assumptions

The responses for the dataset were compiled from a representative cross-section of 450 college students who had experience with AI-assisted learning tools. The participant group is broken down into its component parts, which may be better understood with the help of the demographic information that has been condensed and provided in Table 1. There were 210 male participants, which constitutes 47% of the total, and 240 female participants, which constitutes 53% of the total. This reveals a generally balanced representation of both sexes. The distribution of the cohort throughout different phases of their academic path was highlighted by the academic year distribution, which was as follows: 30% were freshmen, 25% were sophomores, 20% were juniors, and 25% were seniors. The categorization of participants according to their areas of expertise shed light on the multifaceted nature of the academic scene. The sample included 25 people who were majoring in disciplines other than STEM (6%), 150 people who were majoring in business (33%), 90 people who were majoring in the humanities (20%), and 185 people who were majoring in STEM (41%).

Tab. 1: Demographic information of participants (N=450)

Demographic	Category	Frequency	Percentage
Gender	Male	210	47%
	Female	240	53%
Academic Year	Freshman	135	30%
	Sophomore	110	25%
	Junior	90	20%
	Senior	115	25%
Field of Study	STEM	185	41%
	Business	150	33%
	Humanities	90	20%
	Other	25	6%
Age	18-25 years	275	61%
	26-30 years	100	22%
	31-35 years	50	11%
	Over 36 years	25	6%
Prior AI Experience	Frequent	300	67%
	Occasional	150	33%

There was a noticeable tilt in the age distribution that went somewhat more toward the younger age groups. Among the participants, 275 (61%) were between the ages of 18 and 25, 100 (22%) were between the ages of 26 and 30, 50 (11%) were between the ages of 31 and 35, and just 25 (6%) were older than 36. Notably, a sizeable proportion of participants reported having regular experience with AI learning systems. Three hundred participants, or 67% of the total, stated that they routinely used AI-assisted learning systems, whereas just 150 participants, or 33%, reported having occasional experience. The in-depth demographic profile that is shown in Table 2 offers a contextual backdrop against which the outcomes of the research may be interpreted. The purpose of this study is to identify possible trends and differences in how AI assistance interacts with various student profiles by examining the influence of AI-assisted teacher support on learning engagement across gender, academic year, area of study, age groups, and prior experience with AI. This analysis will take into account each participant's prior experience with AI. The capacity of the study to make nuanced conclusions on the impact that AI-assisted assistance has on a variety of student demographics is enhanced by the inclusion of this demographic viewpoint.

Correlation Analysis

To thoroughly examine the correlations between the major variables, a Pearson correlation analysis was performed. This research assessed the degree and direction of these key variables' relationships to reveal patterns and trends. The analytical results and descriptive data have been thoroughly collated and presented in Table 3. The strong and positive association between AI-assisted teacher assistance and learner engagement (0.61) is one of the most notable outcomes of this investigation. This remarkable coefficient shows a strong and positive linear association between students' views of AI tool help and their learning engagement. This shows that students who perceive AI help are more engaged with the content.

Academic self-efficacy relationships also supported the results. Academic self-efficacy positively correlated with AI support ($r = 0.42$) and learning engagement ($r = 0.38$). This suggests that students with higher confidence in their academic talents are more likely to recognize and benefit from AI-assisted teacher assistance, which increases learning material engagement. Additionally, learning type connections were revealed. Despite their smaller size, the associations are statistically significant. Learning styles were somewhat connected with AI support ($r = 0.26$) and learning engagement ($r = 0.28$). This implies a minor but detectable relationship between learning preferences, AI help, and engagement. Overall, these association patterns match the basic predictions well. This early information helps us comprehend these essential factors' favorable correlations. These correlations will be analyzed using multivariate regression to identify any confounding variables and better understand the complex dynamics at play.

Tab. 2: Correlation Matrix for Key Variables

Variable	M	SD	1	2	3	4
AI Support	3.86	0.69	-			
Learning Engagement	3.74	0.72	0.61**	-		
Academic Self-Efficacy	3.49	0.76	0.42**	0.38**	-	
Learning Styles	3.61	0.83	0.26*	0.28*	0.18	-

** $p < 0.01$, * $p < 0.05$

Validation Factor Analysis

The measurement model is robust since the Confirmatory Factor Analysis (CFA) of the questionnaire items' measurement characteristics supports it. All factor loadings from this study are statistically significant and above the 0.5 criterion. This confirms that the observed variables accurately represent their latent components, bolstering the measurement model. The construct dependability values are notable in the results. AI Support has a construct dependability of 0.89, Learning Engagement 0.92, and Academic Self-Efficacy 0.87, indicating good internal consistency in the multi-item measures. This shows that items within each scale regularly form to measure the latent components they represent, boosting the measurement model's trustworthiness. The measurement model's trustworthiness is enhanced by the accurate Average Variance Extracted (AVE). These results show that over half of the variation in the indicators can be assigned to the components they capture, ranging from 0.52 to 0.71. This shows that the measurements capture the substance of their theoretical notions, making the measurement model robust.

When examined in detail, the standardized loadings show each item's proportionate contribution to measuring its construct. LE2 scores best on the Learning Engagement construct, highlighting its importance in measuring this hidden variable. AI3 has the lowest loading on the AI Support construct, indicating a lesser theoretical contribution. The squared multiple correlations show how much each item's variation is explained by its concept, another important analytical step. LE2's high value of 0.77 indicates a strong explanation from this item. These results indicate convergent validity, reliability, and a cohesive factor structure for the measurement scales. This gives the investigation a solid psychometric base and prepares for structural model testing. In conclusion, the CFA results demonstrate that the questionnaire questions properly measure the relevant theoretical structures. These data confirm the validity and suitability of the measures for testing the hypotheses. Table 3: Validation analysis

Tab. 3: Confirmatory Factor Analysis Results

Construct	Item	Standardized Loading	S.E	C.R.	Squared Multiple Correlations
AI Support	AI1	0.71	0.024	14.52	0.5
	AI2	0.77	0.018	15.83	0.59
	AI3	0.68	0.031	12.45	0.46
Learning Engagement	LE1	0.86	0.022	17.14	0.74
	LE2	0.88	0.02	18.24	0.77
	LE3	0.79	0.026	15.33	0.62
Academic Self-Efficacy	SE1	0.74	0.029	13.62	0.55
	SE2	0.8	0.025	14.77	0.64

Construct	Item	Standardized Loading	S.E	C.R.	Squared Multiple Correlations
	SE3	0.69	0.033	12.25	0.48

The Fornell-Larcker Discriminant Validity Criterion Analysis is in Table 4. Displays each construct's AVE and inter-construct correlations. The prominent diagonal components are AVE's square roots. All constructs have AVE square roots that exceed inter-construct correlations. Learning Engagement (0.81) has a higher AVE square root than Career Adaptability (0.62). This finding meets the Fornell-Larcker criteria, establishing construct discriminant validity. This study emphasizes construct uniqueness and enhances the measurement model. Clear presentation of the Fornell-Larcker Criterion Analysis in this tabular style helps readers understand construct linkages and variance explanations. The boldfaced diagonal elements make inter-construct correlation comparisons easy, and the simple textual summary summarizes discriminant validity.

Tab. 4: Fornell-Larcker Criterion Analysis for Discriminant Validity

Construct	AVE	1	2	3
Career Adaptability	0.71	**0.84**		
Learning Engagement	0.65	0.62	**0.81**	
Academic Self-Efficacy	0.57	0.48	0.38	**0.75**

Model Fit Indices for the structural model are in Table 5. The values are compared to the specified thresholds. The $\chi 2/df$ ratio is 2.33, below the required threshold of 5. GFI, AGFI, CFI, NFI, TLI, and RMSEA exceed required levels, indicating strong model fit. The RMSEA of 0.071 is below the threshold limit of 0.08. The cumulative fit indices indicate a strong model-data fit. These results validate the structural model's applicability to the data by demonstrating that it accurately represents construct connections.

Tab. 5: Model Fit Indices

Index	Obtained Value	Recommended Value
$\chi 2/df$	2.33	< 5
GFI	0.91	> 0.90
AGFI	0.88	> 0.80
CFI	0.94	> 0.90
NFI	0.92	> 0.90
TLI	0.93	> 0.90
RMSEA	0.071	< 0.08

Hypothesis Testing Analysis

The investigation of the hypothetical structural model provides convincing evidence that supports the assumptions that were developed, and it also increases our awareness of the complex interrelationships that are included within the research. The findings provide substantial evidence in favor of all three postulated links, highlighting the importance of each proposed route.

Starting with Hypothesis 1, which suggested that AI assistance would have a favorable influence on learning engagement, the standardized coefficient of 0.59 (p .001) strongly confirms the statistical significance of this association. Some researchers have suggested that AI might have a beneficial impact on learning engagement. According to this research, the degree of AI-assisted teacher assistance has a considerable and beneficial affect, both favorably and considerably, on the levels of engagement that students have with the content that they are learning. The consistency of this coefficient lends credence to the idea that the use of AI technologies in educational settings may have a considerable impact on the degree to which students are engaged in the learning process.

The detection of a significant interaction term (= 0.24, p .05) sheds light on Hypothesis 2, which focuses on the moderating influence of academic self-efficacy on the link between AI support and engagement. This result elucidates the existence of a moderating effect, which indicates that the influence of artificial intelligence (AI) assistance on learning engagement is dependant upon the amount of academic self-efficacy exhibited by the students in the study. This discovery sheds light on the complex dynamic at play between the students' sense of their own self-competence and the effectiveness of the artificial intelligence help they get in determining the level of engagement they exhibit.

Moving on to Hypothesis 3, which proposed that learning styles would moderate the correlation between AI support and engagement, the significant coefficient of 0.19 (p .01) strengthens the concept that an individual's learning preferences do indeed alter the degree to which AI support is associated with engagement. This lends credence to the notion that the effectiveness of AI tools is significantly impacted by the degree to which they are aligned with the preferred learning modes of students.

The significant crucial ratios and p-values that are lower than 0.001 are the notable aspects of these findings. These ratios and values indicate that the discovered pathways are not just coincidental but rather have relevant consequences for the study's outcomes. The reliability of the results is high enough that we can say for certain that the connections that have been made are not likely to be the result of random chance.

Tab. 6: Structural Model Hypothesis Testing

Hypothesis	Relationship	Std. Estimate	S.E.	C.R.	p-value
H1	AI Support → Engagement	0.59	0.062	11.33	< .001
H2	AI Support x Self-Efficacy → Engagement	0.24	0.074	3.92	< .05
H3	AI Support x Learning Style → Engagement	0.19	0.088	2.61	< .01

Discussion and Suggestions

Discussion on the Significant Results

The results that were revealed in this research contain significant ramifications, substantiating the essential function that AI-assisted teacher assistance plays in molding the learning engagement of university students. The structural model has been meticulously analyzed, and strong empirical data has been developed as a result. This evidence highlights the large and beneficial effect that AI help has on students' involvement with the learning process. This empirical support is clearly depicted in the considerable standardized path coefficient of 0.59 (p .001), which unquestionably validates the key principle of Hypothesis 1.

However, the implications of these results go beyond the simple correlation between AI assistance and participation in the study. A significant finding emerges in the shape of student characteristics that have a moderating impact on the extent to which this effect is apparent in the data. Empirical support for hypotheses 2 and 3 is found as the research sheds light on the numerous ways in which individual characteristics might have an effect. Notably, academic self-efficacy emerges as a crucial mediator, as students who have a better confidence in their academic ability derive larger advantages from AI technologies. This is an important finding since academic self-efficacy is an important factor. This demonstrates that Hypothesis 2 may be easily supported, and it also suggests that individual beliefs and perceptions have the potential to amplify the effect that AI-assisted teacher assistance has on learning engagement. In addition, the research investigates the field of learning styles and finds that individuals' choices play an important part in the interaction between AI and engagement, providing support for Hypothesis 3. To be more specific, learners who lean more toward activist learning preferences see a more noticeable influence of AI help on their levels of engagement. This dual modulation adds an additional degree of complexity and draws attention to the fact that the effectiveness of AI is inextricably tied to the interaction between individual qualities and technical intervention.

The robustness of the findings is shown by the congruence between these results and previously established ideas on the adoption of technology and individual variations within the context of educational settings. This convergence emphasizes the significance of creating artificial intelligence (AI) systems with an insightful understanding of user characteristics, in order to capitalize on the potential of these technologies to improve student experiences. When taken as a whole, this research marks a big step forward in the process of elucidating the complex web of elements that underlie the connection between AI-facilitated teacher assistance and student involvement in learning. The work lays a strong platform for further inquiries by offering empirical insight into the processes at play. These results not only add to an advancement in our grasp of the complicated dynamics at play within artificial intelligence in education, but they also give a road map for educators and designers who are looking to optimize AI deployments for increased student engagement and outcomes. In conclusion, the findings of this study not only shed light on the current state of affairs but also indicate the way forward for future research into this constantly developing field.

Future Recommendations

The ramifications of these results echo widely inside the sphere of educational practice, giving realistic direction for improving AI systems in a variety of different types of learning contexts. The findings suggesting that student characteristics moderate the relationship between AI and engagement highlights the significance of adaptation. Educational practitioners are strongly urged to build artificial intelligence (AI) systems that dynamically adapt to the varied student profiles that they work with. Students who struggle with poor academic self-efficacy may benefit from having motivational messages and scaffolding included into their coursework. This may be an effective strategy for increasing the students' level of involvement. This individualized strategy takes into account the unique vulnerabilities of each person and customizes treatments to enhance their educational opportunities. In addition, a powerful tactic is emerging as the alignment of various learning styles with the activities that are assisted by AI. Educational practitioners have the potential to get the most possible advantages from AI technologies if they adopt a wide range of instructional modalities that cater to a variety of learners' individual preferences in terms of how they want to learn. This multidimensional strategy has the potential to generate improved engagement and learning outcomes while also expanding the net of influence that may be cast over the whole student population. In addition, this study offers the foundations for future research pathways that might go further into the complex realm of AI in education by providing a foundation for such research. While this study focused on analyzing the relationship between AI support and engagement, it leaves up the possibility of future research investigating other aspects that may have an impact. Researchers are encouraged to look at topics like student-teacher rapport, peer interactions, and classroom environment since these topics have the potential to further deepen our knowledge of this complex ecosystem. It is advised that experimental and longitudinal research designs be used in order to increase the validity of the results. Such an approach would make it possible to draw more certain causal conclusions, so assisting in the uncovering of the complex cause-and-effect interactions that lie at the heart of the influence that AI has on engagement. In addition, broadening the scope of the inquiry to include a variety of educational levels and topic areas would give a full grasp of the ubiquitous nature of AI as well as its complexities.

This study offers the groundwork for a critical foundation upon which further studies might be build, fostering the ongoing path of enhancing AI's potential in educational settings. Because the use of AI in education is still a relatively new phenomena, the views gained from a variety of academic fields may provide light on the intricate workings of this phenomenon. The potential for new discoveries is enormous, and each one has the promise of providing profound insights that may revolutionize instructional strategies.

In summary, the results of this research provide more than simply conclusions; they unveil a landscape of potential for important discoveries that may be made via careful and methodical investigation. Researchers have the ability to usher in an era in which artificial intelligence will change education by working together across disciplines and starting on complete investigations. This will accelerate students toward higher levels of engagement, understanding, and accomplishment.

Conclusion

Artificial intelligence is rapidly changing several industries, including education. AI-powered tutoring systems, adaptive learning platforms, and virtual assistants may improve education. However, AI in education research is still developing. While teacher support has been shown to improve student engagement, motivation, and accomplishment, the processes by which it does so are unclear. This research examined how AI-assisted teacher assistance affects university students' learning engagement to fill this gap.

This study proposed and tested a conceptual model based on self-efficacy theory, flow theory, and constructivism, hypothesising that AI-assisted teacher support positively impacts student learning engagement, depending on academic self-efficacy and learning style. The mixed-methods research tested these assumptions using surveys and interviews. The findings strongly supported the hypothesised correlations. AI-assisted teacher assistance improved student learning engagement. Academic self-efficacy amplified this effect, whereas learning style compatibility strengthened it.

These results affect research and practise. They improve theoretical knowledge of the complicated relationship between AI support systems, individual differences, and engagement results. The research emphasises the necessity for adaptable AI systems that match student profiles and learning styles for educators. This study is a major step towards understanding AI's complex impact on student engagement and achievement. Further research on varied educational settings and levels is needed to progress this rapidly expanding field.

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