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Advancing Learning through Human-Machine Collaboration: Insights from a Meta-Analytic Structural Equation Modelling

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Abstract

Human-Machine Collaborative Learning (HMCL) has gained increasing attention in education due to its potential to enhance learning outcomes through the integration of artificial intelligence (AI) and advanced technologies. This study employed the meta-analytic structural equation model (MASEM) to explore the relationships among the variables in the HMCL, and the data were derived from 15 studies retrieved. The MASEM results show that ease of use, satisfaction level, and learning motivation all positively and significantly influence academic performance, while student satisfaction positively and significantly affects learning motivation. The path coefficients revealed key relationships: ease of use to academic achievement ($\beta = 0.132$), satisfaction to learning motivation ($\beta = 1.354$), satisfaction to academic achievement ($\beta = 0.621$), and learning motivation to academic achievement ($\beta = 0.332$). The MASEM results delineate a clear chain, underscoring the complex interplay between affective, motivational, and cognitive dimensions of learning. Future research should focus on developing robust theoretical frameworks and investigating long-term impacts to further advance HMCL integration into diverse educational contexts.

Keywords: *artificial intelligence in education; human-machine collaborative learning; influence factor; MASEM; structural equation model*

Introduction

With the rapid development of artificial intelligence (AI), machine learning, and big data technologies, the field of education has witnessed transformative innovations in teaching and learning methodologies. Human-Machine Collaborative Learning

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(HMCL) has emerged as a groundbreaking approach, combining human cognitive abilities with the computational power and intelligence of machines to create synergistic and personalized learning experiences. Unlike traditional collaborative learning, which focuses exclusively on human-human interactions, HMCL extends the scope of collaboration to include intelligent systems such as AI-powered chatbots, robots, and adaptive learning platforms. These technologies enable learners to acquire knowledge, develop skills, and co-create new ideas in a dynamic and interactive manner.

The concept of human-machine collaboration can be traced back to the industrial era when workers operated machines for industrial production (Vysocky & Novak, 2016). In the context of education, HMCL initially served as a tool to support learning by providing multimedia resources and interactive content. However, advancements in AI have significantly expanded the applications of HMCL, enabling intelligent systems to provide real-time feedback, personalized recommendations, and adaptive learning paths. These capabilities have shifted HMCL from a supportive role to an active collaborator in the learning process, fostering deeper engagement and understanding among students. However, during this stage, the potential of HMCL was limited due to technological constraints. Learning platforms and tools exhibited lower technological sophistication, lacking a high degree of collaboration and intelligence, limiting students' experience. Nevertheless, significant technological progress has been made in various domains over the past decade. Particularly noteworthy is the remarkable advancement of AI, which has had a transformative impact on the collaborative learning paradigm. Today, HMCL can offer students immediate and intelligent collaboration in their learning process by utilizing AI and big data technologies. This collaborative approach helps learners rectify their errors and receive personalized guidance, thus facilitating a deeper understanding of the subject matter. The primary objective of HMCL is to foster synergistic development between students and machines, thereby contributing to the advancement of education in a more innovative and intelligent direction (Kim & Lee, 2023).

Several researchers have conducted systematic reviews focusing on the tools and hardware employed in collaborative learning. Al-Samarraie and Saeed (2018) systematically reviewed cloud computing tools for collaborative learning in blended classrooms, highlighting the significant impact of such tools on students. Using an adaptive framework based on activity theory, Zheng et al. (2019) conducted a scoping review of collaborative learning in informal learning environments. Their findings revealed an increasing number of studies focused on engineering design tasks, with a greater utilization of mixed-function hardware and software. Peramunugamage et al. (2023) reviewed 48 studies conducted between 2010 and 2020, evaluating the frequency of using different technologies. Their findings indicated that augmented reality and mobile apps were the predominant technologies employed in mobile collaborative learning.

Several scholars have conducted meta-studies of collaborative learning to investigate the impact of tools and strategies on students. Sung et al. (2017) conducted a

meta-analysis of 48 studies on mobile computer-supported collaborative learning (CSCL) and identified significant improvements in collaborative learning, with an overall mean effect size of 0.516. Chen et al. (2018) explored the effectiveness of collaboration, computer use, and support strategies in collaborative learning. Their findings indicated that computer use in collaborative learning environments contributed to the expansion of students' knowledge. Examining the effects of different learning strategies in collaborative learning, Radkowitsch et al. (2020) analyzed the effects of CSCL scripts on students. They found no significant effect on students' motivation to learn but they identified a moderate effect on collaborative skills. Vogel et al. (2017) demonstrated that CSCL scripts served as socio-cognitive scaffolding, with a small positive effect on domain-specific knowledge (d = 0.20) and a significant positive effect on collaborative skills (d = 0.95). Saqr et al. (2022) also discovered that centrality measures in a collaborative setting moderately impacted students' course performance.

In summary, while the development of AI has significantly impacted collaborative learning, prior literature reviews have overlooked the exploration of factors constraining instructional effectiveness in HMCL. Therefore, it is necessary to conduct a comprehensive review of HMCL, especially to focus on the influencing factors of its effects. This study employed the method of meta-analysis structural equation modeling (MASEM) to examine the existing literature on HMCL, in order to comprehensively understand the influencing factors of HMCL and provide insights for future research.

To explore the factors influencing students' academic performance in HMCL, this study draws upon the Technology Acceptance Model (TAM) (Davis, 1989) and Self-Determination Theory (SDT) (Deci & Ryan, 2000). The TAM foundation allows this study to posit that students' perceptions of ease of use (EOU) and usefulness (US) are critical precursors to their satisfaction (SA). Complementarily, SDT provides a lens to understand how this satisfaction can foster learning motivation (LM) by supporting learners' innate psychological needs for autonomy, competence, and relatedness, thereby creating the conditions for enhanced academic performance (AP). Synthesizing these two frameworks offers a more holistic pathway from technology perception to academic achievement. Based on this integrated perspective, the following hypotheses are proposed.

The relationship among EOU, LM and AP

EOU refers to the degree to which an individual believes that using a particular system would be effortless (Vlachogianni & Tselios, 2022). When students perceive HMCL systems or tools as easy to navigate and operate, they are more likely to experience reduced cognitive load and increased willingness to engage in learning tasks, thereby enhancing their LM. Previous studies have also indicated a positive correlation between ease of use and motivation in e-learning environments (Herrero-Álvarez et al., 2024).

When other conditions are equal, HMCL systems that are more intuitive, user-friendly, and interactive are more likely to be accepted and continuously used by

students. Such a seamless experience not only improves learning efficiency but also allows students to invest more cognitive effort in the learning content itself (Xiao & Adnan, 2022). A substantial body of literature has confirmed a significant positive relationship between EOU and AP (Tselegkaridis et al., 2025). When a HMCL system is considered easy to use, students are more inclined to explore its features actively, which facilitates deeper engagement with learning resources and more effective knowledge construction (Álvarez-Marín et al., 2023).

Hypothesis 1: EOU has a significant positive influence on AP.

Hypothesis 2: EOU has a significant positive influence on LM.

The relationship between US, LM and AP

US is a cornerstone construct of the Technology Acceptance Model. In educational contexts, it refers to students' subjective assessment of the extent to which a specific instructional approach or intelligent tool enhances their learning effectiveness and efficiency (El-Sayad et al., 2021). In HMCL environments, this perception evolves beyond the utility of basic functionalities – such as content delivery and interactive feedback – to encompass the perceived value of the human–AI complementary mechanisms. Students evaluate whether the AI partner augments their capabilities, fills cognitive gaps, and ultimately provides a unique advantage that would be absent in traditional learning settings.

The relationship between US and AP has been well established in prior research (Harks et al., 2014; Hwang et al., 2011; Shin et al., 2020). When students believe that a given learning method or tool helps them better understand concepts and improves their learning efficiency, they are more likely to achieve better academic outcomes (Ganotice & Chan, 2019).

Hypothesis 3: US has a significant positive influence on AP.

Hypothesis 4: US has a significant positive influence on LM.

The relationship among SA, LM and AP

Satisfaction reflects students' subjective evaluation of the overall learning experience (Wong & Chapman, 2023). It not only represents their recognition of the system's functions and services but also embodies the psychological perception of being supported, understood, and respected during the learning process. A satisfying learning experience can significantly enhance students' positive emotions, reduce anxiety and frustration, and thereby further stimulate their motivation to learn (James, 2021).

Therefore, in HMCL environments, student satisfaction is not only a critical metric for system evaluation but also a key psychological variable influencing both LM and AP. Studies have shown that higher levels of satisfaction can effectively increase students' emotional engagement in the learning process and enhance their AP (Pan et al., 2025). Empirical research has also found that satisfaction may influence academic

achievement not only through indirect pathways (e.g., via motivation) but also, in certain contexts, through a direct positive effect (Innab et al., 2022).

Hypothesis 5: SA has a significant positive influence on AP.

Hypothesis 6: SA has a significant positive influence on LM.

The relationship between LM and AP

LM is widely recognized as a central determinant of academic success, serving as a key psychological mechanism that drives and sustains the efforts necessary to achieve desirable academic outcomes (Gopalan et al., 2017).

The influence of LM on AP can be understood through several key mechanisms. Primarily, motivation stimulates students' intrinsic interest in knowledge and their inherent desire to explore, thereby promoting active and deep engagement in the learning process (Kong, 2021). According to Self-Determination Theory (Deci & Ryan, 2000), when students' innate psychological needs for autonomy, competence, and relatedness are satisfied, their intrinsic motivation is enhanced, leading to higher quality learning and improved performance. Furthermore, highly motivated students are more likely to set specific and challenging personal learning goals, diligently monitor their progress, and proactively adjust their learning strategies when faced with difficulties (Rahimi & Cheraghi, 2024; Wilby, 2022; Zheng et al., 2021). This process is closely linked to the use of metacognitive strategies and greater academic persistence, enabling students to overcome challenges and optimize their learning outcomes. Therefore, LM is not merely a complementary factor but a critical and powerful variable that significantly influences learning effectiveness and academic achievement.

Hypothesis 7: LM has a significant positive influence on AP.

Methodology

Analysis tool

The selected tools for this study are Comprehensive Meta-Analysis (CMA) and Analysis of Moment Structures (AMOS). CMA is a tool specifically designed for conducting meta-analyses. It provides researchers with various functions, including effect size calculations, forest plot generation, and subgroup analysis (Wallace et al., 2009; Almassri & Zaharudin, 2023). AMOS is a software for structural equation model analysis, used to explore the path relationships among variables (Arbuckle & Wothke, 1999).

Inclusion criteria

The following inclusion criteria were applied to the selected literature to screen for the meta-analysis:

1 The subject of the study must be the impact or effect of HMCL on students.

2 The study must adhere to an experimental design.

3 The study reported detailed and specific statistical information on the experimental data, such as the sample size, mean, and correlation, which enabled the calculation of the corresponding effect value of the study.

Article selection process

The article sources for this study include Web of Science (WoS), Scopus, and EBSCO. A comprehensive search was conducted using the keywords "student" or "human" and "machine" or "computer" or "robot" or "artificial intelligence" or "AI" and "collaborative learning" or "collaboration learning." The search was limited to articles published between January 2013 and May 2025, written in English, and classified as "Article" type. Ultimately, a total of 15 articles were selected for analysis. The articles were thoroughly reviewed, eliminating articles with uncontrolled experiments and incomplete data reports. The literature screening process is illustrated in Figure 1.

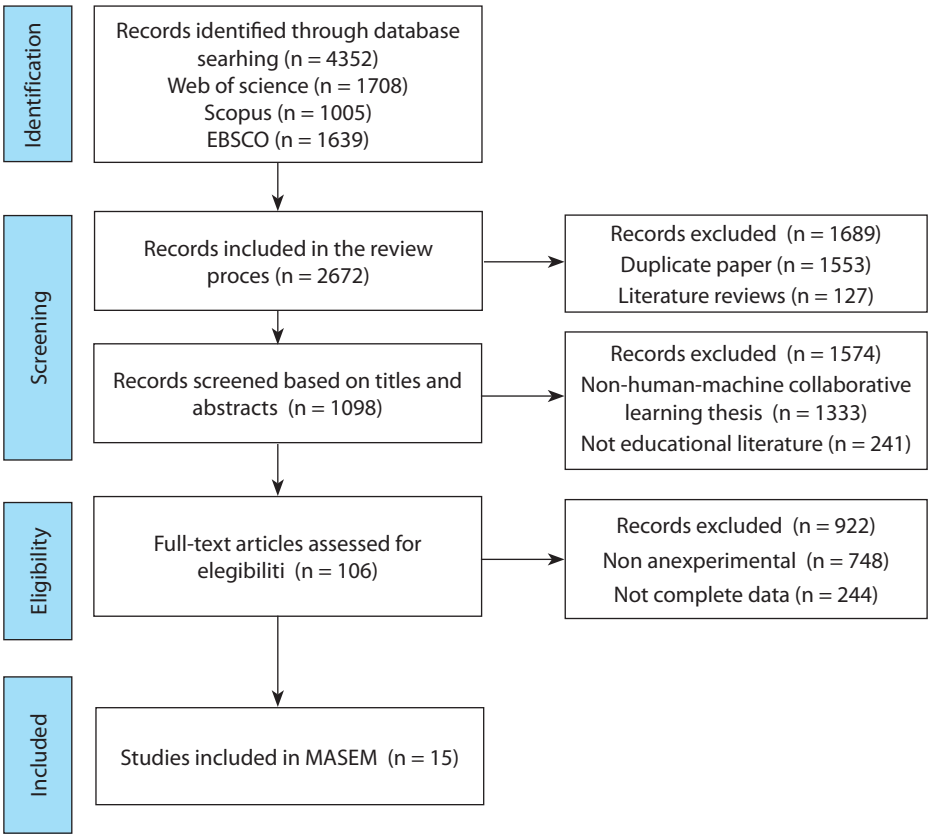


Figure 1. Article selection process for bibliometric analysis

Publication bias and heterogeneity assessment

The heterogeneity observed in the effect sizes considered in the meta-analysis can be attributed to variations in study design, experimental subjects, and measurement tools across the literature included in the analysis (Higgins & Thompson, 2002). As a result, a heterogeneity test was carried out in this study. The level of heterogeneity in the meta-analysis sample was assessed using the I^2 statistic (with values of 25 %,

50 %, and 75 %, corresponding to low, medium, and high degrees of heterogeneity, respectively), Q statistics, and their significance ($p<0.05$) (Whitehead & Whitehead, 1991). The results of the heterogeneity detection in the meta-analysis samples revealed a Q-statistic value of 112.682, which significantly exceeded the degrees of freedom (df = 25), indicating statistical significance ($p<0.001$). Moreover, the I^2 value was 77.81 %, surpassing the 75 % threshold, indicating a high level of heterogeneity among the meta-analysis samples. Consequently, a random-effects model was employed for the statistical analysis and subsequent study assessment (Borenstein et al., 2009) to ensure the accuracy and reliability of the findings.

Results

Quality assessment

The quality evaluation of the included literature was conducted using the criteria outlined in the Cochrane Handbook (Higgins & Green, 2008) for trials. The assessment criteria included randomization, allocation concealment, blinding, data completeness, selective reporting of results, and other potential biases. The results of the risk of bias assessment for the included studies are depicted in Figure 2. It was found that the risk of bias for selective reporting was low for all studies, with no mention of missing data.

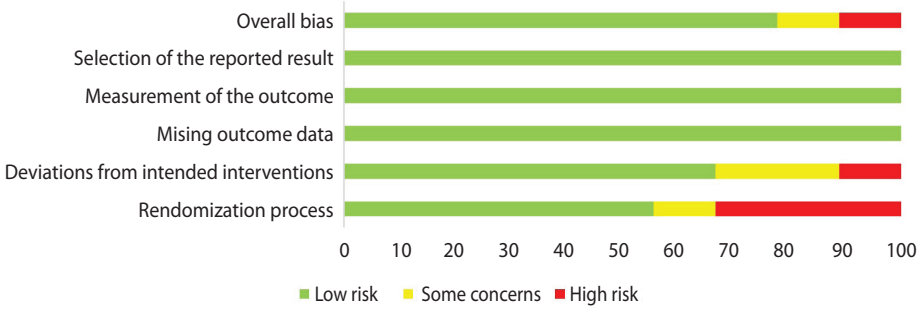


Figure 2. Migration risk ratio chart

Heterogeneity test of structural equation models

Heterogeneity was tested using the I^2 statistic. The I^2 values for included studies were relatively high, and the corresponding p-values were lower than 0.001 (see Table 1), indicating a lack of homogeneity among the relationships. Therefore, a random-effects model was adopted to calculate the overall weighted mean correlation coefficients. This study employed Rosenthal's loss of safety coefficient method for bias testing (Rosenthal, 1986). If the loss safety factor exceeds the threshold of 5K + 10, it can be determined that there is no obvious bias. Therefore, the samples included in this study have almost no bias interference. Table 1 also presents detailed parameters for each relationship, including correlation coefficients, confidence intervals, and fail-safe N values.

Table 1
Dual-variable Correlation Analysis

Relationship	Number of papers	Sample	Weighted mean correlation		95 % Confidence interval		I^2	Fail-safe N
			Corr	SE	Lower limit	Upper limit		
EOU→AP	2	704	0.607***	0.098	0.447	0.729	84.66	NA
EOU→LM	2	412	0.404	0.235	-0.059	0.724	95.69	NA
EOU→SA	3	1063	0.716***	0.045	0.658	0.766	59.23	582
LM→AP	4	757	0.695***	0.084	0.574	0.786	85.57	548
LM→SA	4	985	0.695***	0.075	0.589	0.777	87.02	705
SA→AP	3	1146	0.786***	0.118	0.635	0.88	95.35	1309
US→AP	3	839	0.595***	0.033	0.545	0.64	9.23	267
US→EOU	5	1227	0.629***	0.088	0.49	0.736	89.88	764
US→LM	4	945	0.510***	0.089	0.355	0.638	87.82	300
US→SA	3	1063	0.739***	0.097	0.608	0.832	91.52	701

Note: Fail-safe N represents the fail-safe number. *** indicates $P < 0.001$.

The result of the correlation coefficient test

This study examined the overall correlations between pairs of variables and, on this basis, constructed a correlation coefficient matrix, as shown in Table 2. The off-diagonal values represent the mean correlation coefficients weighted by average sample size.

Table 2
Correlation matrix for MASEM

Construct	AP	EOU	LM	SA	US
AP	1				
EOU	0.607	1			
LM	0.695	0.404	1		
SA	0.786	0.716	0.695	1	
US	0.595	0.629	0.51	0.739	1

Results of the structural equation model

In the meta-analytic correlation matrix, effect sizes were calculated based on varying sample sizes across different studies, whereas MASEM typically requires analysis based on a unified sample size. Therefore, to account for this discrepancy and minimize potential biases caused by large variations in sample sizes, the harmonic mean of the sample sizes was used in this study, resulting in an effective sample size of 833.123. The correlation matrix was then imported into AMOS 24.0 for structural equation model analysis, with reliability coefficients taken into account. For constructs where reliability was not reported in the original studies, a default reliability value of 0.80

was applied, based on the recommendations of Dalton et al. (1998). The results of the structural model fit are presented in Table 3.

Table 3
The fitting result of the structural model

Hypothetical relationship	Estimate	SE	CR	P
H1: EOU→AP	0.132	0.070	1.898	0.058
H2: EOU→LM	-0.507	0.069	-7.330	***
H3: US→AP	-0.136	0.058	-2.358	0.018
H4: US→LM	-0.161	0.074	-2.195	0.028
H5: SA→AP	0.621	0.138	4.506	***
H6: SA→LM	1.354	0.094	14.405	***
H7: LM→AP	0.332	0.073	4.559	***

Based on the established correlation coefficient matrix, structural equation model was further employed to analyze the multivariate path relationships among the variables. The path analysis was conducted using AMOS 24.0, and the structural model is illustrated in Figure 3. As shown in the figure, the path coefficient from EOU to AP is 0.132. The path coefficient from SA to LM is 1.354, while the coefficient from SA to AP is 0.621. Additionally, the path coefficient from LM to AP is 0.332.

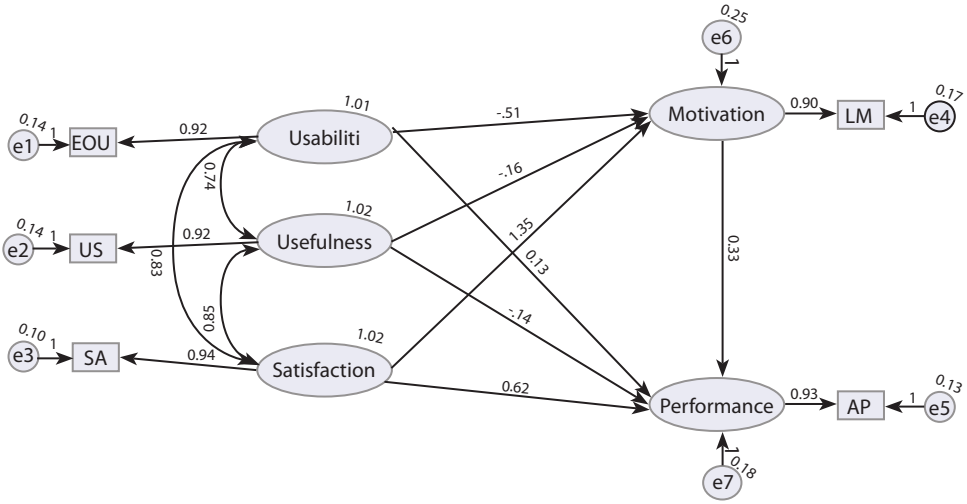


Figure 3. MASEM results for the proposed model

Discussion

The analysis revealed that the path from SA to LM exhibited the strongest effect size (β = 1.35), powerfully emphasizing learner satisfaction as a paramount predictor of subsequent motivational engagement. This finding is consistent with the findings

of Wang et al. (2021), who identified a similar robust link in their investigation of cloud-based virtual teachers, and it further aligns with a growing body of research stressing the critical role of learner-related affective factors in distance and technology-mediated education (Yalçınkaya, 2024). Theoretically, this robust relationship lends strong support to the principles of Self-Determination Theory (Ryan & Deci, 2000). It supports the notion that positive emotional experiences and satisfaction in learning environments are not merely peripheral benefits but are fundamental to fulfilling learners' basic psychological needs for autonomy, competence, and relatedness, which in turn significantly enhances intrinsic motivation (Leon, 2018). In the context of HMCL, student satisfaction likely stems from the perceived seamlessness of the collaboration, the reliability of AI, and the sense of accomplishment it facilitates, all of which fuel the desire to learn.

Furthermore, LM was confirmed as a direct, positive predictor of AP ($\beta = 0.33$), a result that corroborates a vast corpus of earlier educational research (Chang, 2019; Chen & Tu, 2021; Meng & Hu, 2022). The underlying mechanism for this relationship is well-understood: motivated learners typically demonstrate greater cognitive persistence when confronting challenging material, superior self-regulation in managing their learning processes, and more consistent goal-directed behavior. These attributes directly facilitate a deeper understanding of subject matter and more effective knowledge application, all of which are key contributors to improved academic achievement (Sia et al., 2024; Zhou & Zhang, 2024).

A particularly insightful finding from the model is the nature of the relationship between SA and AP. Notably, while the direct path coefficient from SA to AP was itself relatively strong ($\beta = 0.62$), the presence of a significant indirect effect through LM suggests a partially mediated relationship. This indicates that SA influences AP through a dual-channel mechanism: it has a direct effect, potentially by reducing learning anxiety and creating a cognitive state conducive to knowledge absorption, and it exerts a powerful indirect effect by first bolstering the learner's intrinsic and extrinsic motivation, which then propels academic effort and success. This partial mediation highlights that while a positive SA can immediately benefit performance, a substantial portion of its impact is channeled through the sustained energy and LM that it inspires.

EOU and US are recognized as core constructs of the TAM (Davis, 1989). However, the findings of this study indicate that, within the HMCL context, these factors exert relatively limited direct positive effects on students' AP. Previous empirical studies have provided converging evidence supporting this situation. Chen et al. (2025) found that EOU did not significantly influence LM, nor did it positively predict AP. Similarly, Sarwar et al. (2019) reported that EOU had no significant positive effect on collaborative learning. In addition, Nugroho et al. (2018) demonstrated that both US and EOU failed to significantly predict students' academic achievement. As AI-supported tools have become increasingly standardized and user-friendly, EOU

and US may gradually evolve into baseline expectations rather than decisive factors influencing AP (Dwivedi et al., 2021). In such contexts, these perceptual constructs are less likely to directly differentiate learning outcomes, as users tend to assume a minimum level of usability and functionality. Instead, their influence may be realized indirectly through other psychological and behavioral mechanisms (Al-Emran et al., 2018). EOU and US should be redefined as fundamental conditions in the intelligent learning environment, rather than being regarded as direct predictors of students' AP.

Collectively, these SEM results illuminate the dynamic and synergistic interplay between the technological support system—the "Machine" in HMCL—and the learner's internal psychological factors in co-shaping academic success. The technological tool's value is not merely functional but is deeply psychological, operating through the pathways of satisfaction and motivation (Nguyen et al., 2019). Consequently, this study argues that future research, instructional design, and the evaluation of educational technologies must move beyond a purely functional assessment. There is a compelling need to more deeply and intentionally integrate the fostering of positive emotional experiences and the support of motivational processes into the very fabric of educational technology development (Wang et al., 2022).

To fully harness the potential of technology, educators and developers must design HMCL environments that are not only effective but also fundamentally satisfying and motivating. Blended learning has positively impacted student learning (Rasheed et al., 2020). Integrating blended learning into HMCL environments enables teachers to personalize their instruction and provide targeted feedback by monitoring students' real-time performance through online platforms. This approach creates a more engaging learning experience that enhances student interest and motivation (Suryono et al., 2023; Ustun et al., 2023). On the other hand, group learning, a crucial facet of HMCL, highlights the importance of collaborative learning in knowledge construction and sharing. Through group learning, students can exchange diverse perspectives, experiences, and strategies, which enriches their understanding of the subject matter and facilitates deeper learning. Learning tasks should also be designed to foster thinking, analysis, and problem-solving (Sabo Junger et al., 2024). By creating problem-based scenarios, teachers can stimulate students' positive emotions (Saygili Yildirim & Sahin Izmirli, 2024). Educators should intensify their efforts to explore the potential of blended and group learning in HMCL practice and continue to innovate their instructional design. Teachers should enhance their technological literacy and use computer technologies appropriately (Miljković Krecar & Pavlin-Bernardić, 2025). Chatbots, online learning platforms, and cooperative systems are all significant facilitators for student learning. In recent years, chatbots have gained widespread usage in online learning environments, serving as intelligent programs capable of simulating human dialogue (Kuhail et al., 2023). Firstly, chatbots provide real-time learning support and personalized answers to help students overcome their learning challenges, thereby enhancing the efficiency of the learning process. Secondly, by leveraging natural

language processing technology, chatbots engage in interactive dialogues with students, injecting liveliness and interactivity into the learning experience (Kasthuri & Balaji, 2023). This interactivity contributes to heightened student interest and engagement in learning, fostering a more compelling learning experience. AI algorithms can be used to predict student dropout and support sustained learning (Spalević et al., 2025). Educators can strategically integrate these technologies to augment student learning engagement (Viberg et al., 2023).

This research provides a direction for future studies on HMCL and investigates the effectiveness of HMCL in teaching practice, emphasizing the significance of technical and emotional factors in promoting students' learning motivation and ultimate academic success. It is expected to offer valuable guidance, serving as a reference for researchers exploring and selecting research topics related to HMCL.

The limitations of this study must be acknowledged. The inclusion criteria were limited to articles with complete reports, excluding studies with only abstracts or briefs. Additionally, the analysis was restricted to articles written in the English language. During the process of modeling structural equations, some studies failed to guarantee complete reliability. Future research endeavors should incorporate a broader range of moderating variables and conduct comprehensive investigations to deepen our understanding of their impact. Researchers should be encouraged to engage into multilingual literature research and adopt a broader analysis to ensure a comprehensive understanding of HMCL.

Conclusion

The results of the current study suggest significant implications for research and practice. This study used MASEM methods to comprehensively investigate the existing literature on HMCL, aiming to gain a comprehensive understanding of HMCL influencing factors. A literature search was conducted on articles written from 2013 to 2025 using Web of Science, Scopus, and EBSCO databases, and 15 articles were selected to construct structural equation models. The results of the structural equation modeling revealed several significant pathways among key variables. The model identified SA as the primary driver in the framework, exerting a powerful influence on both LM and AP. Concurrently, LM confirmed its role with a significant positive influence on AP. MASEM relies on the systematic synthesis of correlation matrices reported in prior empirical studies, which serve as the foundational input for estimating structural relationships at a meta-analytic level. Future research should incorporate a larger body of empirical studies, apply more rigorous bias diagnostic methods, and explore longitudinal and experimental designs to further validate the findings.

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Ostvarivanje napretka u učenju suradnjom čovjeka i stroja: saznanja dobivena metaanalitičkim modeliranjem strukturne jednadžbe

Sažetak

Učenje temeljeno na suradnji čovjeka i stroja privuklo je veliku pozornost u području obrazovanja jer ima potencijal da poveća usvojenost ishoda učenja putem integracije umjetne inteligencije i naprednih tehnologija. U ovome je istraživanju korišteno metaanalitičko modeliranje strukturne jednadžbe kako bi se ispitala veza između varijabli u učenju temeljenom na suradnji čovjeka i stroja. Podatci za analizu dobiveni su iz 15 odabranih studija. Rezultati metaanalitičkoga modeliranja strukturne jednadžbe pokazuju da lakoća korištenja, razina zadovoljstva te motivacija za učenje imaju pozitivan i značajan utjecaj na akademska postignuća, dok zadovoljstvo studenata pozitivno i značajno utječe na motivaciju za učenje. Koeficijenti putanje otkrili su ključne veze između: lakoće korištenja i akademskih postignuća (β = 0,132), zadovoljstva i motivacije za učenje (β = 1,354), zadovoljstva i akademskih postignuća (β = 0,621) te motivacije za učenje i akademskih postignuća (β = 0,332). Rezultati metaanalitičkoga modeliranja strukturne jednadžbe pokazuju jasan lanac, naglašavajući složenu interakciju između afektivne, motivacijske i kognitivne dimenzije učenja. Buduća bi se istraživanja trebala usmjeriti na izradu čvrstih teorijskih okvira i istraživanje dugoročnih utjecaja kako bi se unaprijedila daljnja integracija učenja temeljenoga na suradnji čovjeka i stroja u različite obrazovne kontekste.

Ključne riječi: *faktori utjecaja; metaanalitičko modeliranje strukturne jednadžbe; model strukturne jednadžbe; učenje temeljeno na suradnji čovjeka i stroja; umjetna inteligencija u obrazovanju*

Uvod

U područje obrazovanja unesene su mnogobrojne inovacije koje su transformirale načine poučavanja i učenja, a koje su rezultat izuzetno brzoga napretka u razvoju umjetne inteligencije (UI), učenja pomoću stroja te tehnologija koje obrađuju velike

količine podataka. Učenje temeljeno na suradnji čovjeka i stroja pojavilo se kao iznimno inovativan pristup jer kombinira ljudske kognitivne sposobnosti i računalnu moć i inteligenciju stroja kako bi se stvorila sinergijska i personalizirana iskustva učenja. Za razliku od tradicionalnoga suradničkog učenja, koje je usmjereno isključivo na interakciju između čovjeka i stroja, učenje temeljeno na suradnji čovjeka i stroja proširuje opseg suradnje tako što uključuje sustave poput *chatbotova* koji koriste umjetnu inteligenciju, robota te prilagodljivih platformi za učenje. Navedene tehnologije omogućavaju studentima usvajanje znanja, razvijanje vještina i zajedničko stvaranje ideja na dinamičan i interaktivan način.

Pojam suradnje čovjeka i stroja potječe od industrijske ere kada su radnici upravljali strojevima u industrijskoj proizvodnji (Vysocky i Novak, 2016). U obrazovnom kontekstu, učenje temeljeno na suradnji čovjeka i stroja prvo je služilo kao alat koji pomaže pri učenju tako što omogućava pristup multimedijalnim izvorima i interaktivnim sadržajima. Međutim, napredak u razvoju umjetne inteligencije značajno je proširio raspon primjene učenja temeljenoga na suradnji čovjeka i stroja, što je omogućilo inteligentnim sustavima pružanje povratnih informacija u stvarnom vremenu, personalizirane preporuke i prilagodljive načine učenja. Te su mogućnosti transformirale ulogu učenja temeljenoga na suradnji čovjeka i stroja od sporedne uloge u ulogu aktivnoga suradnika u procesu učenja, što je rezultiralo većom uključenošću studenata i boljim razumijevanjem. Međutim, tijekom ove faze, potencijal učenja temeljenoga na suradnji čovjeka i stroja bio je sužen zbog tehnoloških ograničenja. Platforme i alati za učenje imali su nižu razinu tehnološkoga razvoja te im je nedostajao viši stupanj suradnje i inteligencije, a to je studentima ograničavalo iskustvo učenja. Ipak, tijekom prošloga desetljeća ostvaren je značajan tehnološki napredak u različitim domenama. Posebno je bitno istaknuti izvanredan napredak umjetne inteligencije koja je transformirala paradigmu suradničkoga učenja. Danas učenje temeljeno na suradnji čovjeka i stroja može studentima omogućiti neposrednu i inteligentnu suradnju u procesu učenja primjenom umjetne inteligencije i tehnologije velikih podataka. Ovakav im suradnički pristup pomaže ispraviti pogreške i dobiti personaliziranoga vodiča te se tako omogućava bolje razumijevanje određenoga predmetnog sadržaja. Glavni je cilj učenja temeljenoga na suradnji čovjeka i stroja stvoriti sinergiju između studenta i stroja i tako doprinijeti razvoju obrazovanja u inovativnijem i pametnijem smjeru (Kim i Lee, 2023).

Nekoliko je autora sustavno analiziralo alate i *hardware* koji se koriste u suradničkome učenju. Al-Samarraie i Saeed (2018) detaljno su analizirali alate koji su u računalstvu u oblaku dostupni za suradničko učenje u mješovitim učionicama, naglašavajući njihov značajan utjecaj na studente. Koristeći prilagodljivi okvir izrađen na temelju teorije o aktivnosti, Zheng i sur. (2019) proveli su sveobuhvatni pregled literature o suradničkom učenju u neformalnom okružju za učenje. Njihovi su rezultati pokazali povećanje broja istraživanja usmjerenih na zadatke inženjerskoga dizajna, uz veću uporabu *hardwarea*

i *softwarea* mješovitih funkcija. Peramunugamage i sur. (2023) analizirali su 48 studija provedenih u razdoblju između 2010. i 2020. godine i procijenili učestalost korištenja različitih tehnologija. Njihovi su rezultati pokazali da su proširena stvarnost i mobilne aplikacije najviše korištene tehnologije u mobilnome suradničkom učenju.

Nekoliko je znanstvenika provelo metastudije o suradničkom učenju kako bi ispitali utjecaj alata i strategija na studente. Sung i sur. (2017) proveli su metaanalizu koja je obuhvatila 48 studija o mobilnom suradničkom učenju podržanom računalom i uočili značajan napredak u suradničkom učenju, s općom srednjom veličinom učinka od 0,516. Chen i sur. (2018) proveli su istraživanje o učinkovitosti suradnje, upotrebe računala te strategija podrške u suradničkom učenju. Njihovi rezultati pokazuju da je upotreba računala u okružju za suradničko učenje doprinijela povećanom znanju studenata. Radkowitsch i sur. (2020) analizirali su utjecaj scenarija računalno podržanoga suradničkog učenja na studente, ispitujući učinkovitost različitih strategija učenja u suradničkom okružju. Nisu uočili značajan utjecaj na motivaciju studenata za učenje, ali su utvrdili umjeren utjecaj na suradničke vještine. Vogel i sur. (2017) pokazali su da scenariji računalno podržanoga suradničkoga učenja služe za postupnu izgradnju sociokognitivnih sposobnosti, uz mali pozitivan utjecaj na znanje o specifičnoj domeni (d = 0,20) i značajan pozitivan utjecaj na suradničke vještine (d = 0,95). Saqr i sur. (2022) također su došli do saznanja da mjere centralnosti u suradničkom okružju umjereno utječu na uspjeh studenata u određenome kolegiju.

Može se zaključiti da, iako je razvoj umjetne inteligencije imao značajan utjecaj na suradničko učenje, ranije analize literature previdjele su važnost analize faktora koji ograničavaju učinkovitost nastave u učenju temeljenom na suradnji čovjeka i stroja. Stoga je potrebno provesti sveobuhvatan pregled učenja temeljenoga na suradnji čovjeka i stroja, s posebnim naglaskom na faktore koji na njega uvelike utječu. U ovome je istraživanju primijenjena metoda metaanalitičkoga modeliranja strukturne jednadžbe za analizu postojeće literature o učenju temeljenom na suradnji čovjeka i stroja kako bi se detaljno mogli razumjeti faktori koji na njega utječu i dobile smjernice za buduća istraživanja.

S ciljem ispitivanja faktora koji utječu na akademska postignuća studenata u učenju temeljenom na suradnji čovjeka i stroja, u ovome su istraživanju uključeni model prihvaćanja tehnologije (TAM) (Davis, 1989) i teorija samoodređenja (SDT) (Deci i Ryan, 2000). Na temelju modela prihvaćanja tehnologije u istraživanju se kreće od pretpostavke da su percepcije studenata o lakoći korištenja i korisnosti glavni indikatori njihova zadovoljstva. Uz to, teorija samoodređenja pomaže nam lakše razumjeti kako zadovoljstvo može ojačati motivaciju za učenje pružanjem podrške za unutarnje psihološke potrebe studenata za autonomijom, kompetencijama i povezanošću. Tako se stvaraju uvjeti za bolji akademski uspjeh. Sinteza ovih dvaju okvira otvara mogućnost cjelovitijeg napretka od načina na koji studenti percipiraju tehnologiju ka akademskim postignućima. Na temelju ove integrirane perspektive, predlažu se sljedeće hipoteze.

Veza između lakoće korištenja, motivacije za učenje i akademskih postignuća

Pod lakoćom korištenja podrazumijeva se stupanj uvjerenja osobe da će korištenje određenoga sustava biti vrlo lako (Vlachogianni i Tselios, 2022). Kada studenti smatraju da će se sustavima ili alatima za učenje temeljeno na suradnji čovjeka i stroja lako koristiti i lako se snalaziti u njima, veća je vjerojatnost da će osjetiti reducirano kognitivno opterećenje i biti spremniji za sudjelovanje u zadatcima, čime će se povećati njihova motivacija za učenje. Ranija su istraživanja također pokazala pozitivnu korelaciju između lakoće korištenja i motivacije u okružju za učenje pomoću računala (Herrero-Álvarez i sur., 2024).

Kada su drugi uvjeti jednaki, sustave učenja temeljenoga na suradnji čovjeka i stroja koji su intuitivniji, interaktivniji i koje je lakše koristiti studenti će u većoj mjeri prihvatiti i kontinuirano koristiti. Takvo jednostavno iskustvo ne samo da poboljšava učinkovitost učenja, nego i pomaže studentima uložiti veći kognitivni trud u sadržaje koje uče (Xiao i Adnan, 2022). Znatan dio literature potvrdio je značajnu pozitivnu vezu između lakoće korištenja i akademskih postignuća (Tselegkaridis i sur., 2025). Kada smatraju da je sustav učenja temeljenoga na suradnji čovjeka i stroja lako koristiti, studenti se aktivno uključuju u istraživanje njegovih mogućnosti, što omogućava bolju interakciju s izvorima učenja i učinkovitiju izgradnju znanja (Álvarez-Marín i sur., 2023).

Hipoteza 1: Lakoća korištenja ima značajan pozitivan utjecaj na akademska postignuća.

Hipoteza 2: Lakoća korištenja ima značajan pozitivan utjecaj na motivaciju za učenje.

Veza između korisnosti, motivacije za učenje i akademskih postignuća

Korisnost je temeljni konstrukt u modelu prihvaćanja tehnologije. U obrazovnim kontekstima, ona podrazumijeva subjektivnu procjenu studenata o tome u kojoj mjeri određeni nastavni pristup ili pametni alat povećava učinkovitost i učinak njihova učenja (El-Sayad i sur., 2021). U okružju za učenje temeljeno na suradnji čovjeka i stroja, ovakva percepcija nadilazi korisnost osnovne funkcionalnosti, poput kreiranoga sadržaja ili interaktivne povratne informacije te obuhvaća percipiranu vrijednost komplementarnih mehanizama između čovjeka i umjetne inteligencije. Studenti procjenjuju povećava li umjetna inteligencija njihove sposobnosti, popunjava li kognitivne praznine te predstavlja li jedinstvenu prednost koja ne bi postojala u tradicionalnim okružjima za učenje.

Veza između korisnosti i akademskih postignuća već je uočena u ranijim istraživanjima (Harks i sur., 2014; Hwang i sur., 2011; Shin i sur., 2020). Kada studenti smatraju da im određena metoda učenja ili alat za učenje pomažu bolje shvatiti pojmove i poboljšati učinkovitost u učenju, postoje veći izgledi da će im akademska postignuća biti bolja (Ganotice i Chan, 2019).

Hipoteza 3: Korisnost ima značajan pozitivan utjecaj na akademska postignuća.

Hipoteza 4: Korisnost ima značajan pozitivan utjecaj na motivaciju za učenje.

Veza između zadovoljstva, motivacije za učenje i akademskih postignuća

Zadovoljstvo odražava subjektivnu procjenu studenata o općem iskustvu učenja (Wong i Chapman, 2023). Ono izražava ne samo njihovo prepoznavanje funkcija i usluga koje sustav nudi, nego i psihološku percepciju o podršci koja im je dostupna, razumijevanju na koje nailaze te poštovanje koje im se iskazuje tijekom procesa učenja. Zadovoljstvo iskustvom učenja može značajno povećati razinu pozitivnih emocija, smanjiti anksioznost i frustracije te tako dalje stimulirati motivaciju za učenje (James, 2021).

Stoga u okružju za učenje temeljenom na suradnji čovjeka i stroja zadovoljstvo studenata nije samo kritička mjera za sustav evaluacije, nego i ključna psihološka varijabla koja obuhvaća motivaciju za učenje i akademska postignuća. Istraživanja su pokazala da veća razina zadovoljstva može učinkovito djelovati na povećanje emocionalne uključenosti studenata u proces učenja te im povećati akademska postignuća (Pan i sur., 2025). Empirijska su istraživanja također pokazala da zadovoljstvo može utjecati na akademska postignuća ne samo posrednim mehanizmima (npr. putem motivacije), nego u nekim kontekstima i izravnim pozitivnim utjecajem (Innab i sur., 2022).

Hipoteza 5: Zadovoljstvo ima značajan pozitivan utjecaj na akademska postignuća.

Hipoteza 6: Zadovoljstvo ima značajan pozitivan utjecaj na motivaciju za učenje.

Veza između motivacije za učenje i akademskih postignuća

Motivacija za učenje uvelike je prepoznata kao središnja odrednica akademskoga uspjeha, a služi i kao ključni psihološki mehanizam koji stvara i podržava trud potreban za postizanje poželjnih akademskih ishoda (Gopalan i sur., 2017).

Utjecaj motivacije za učenje na akademska postignuća može se razumjeti na temelju nekoliko ključnih mehanizama. Kao prvo, motivacija potiče intrinzični interes studenata za znanje i njihovu prirodnu želju za istraživanjem. Tako se potiče aktivno i duboko uključivanje u proces učenja (Kong, 2021). Prema teoriji saomoodređenja (Deci i Ryan, 2000), kada su urođene psihološke potrebe studenata za autonomijom, kompetencijama i povezanošću zadovoljene, njihova se intrinzična motivacija povećava i vodi do kvalitetnijega učenja i boljih rezultata. Nadalje, visoko motivirani studenti u većoj mjeri određuju specifične i zahtjevnije osobne ciljeve učenja, marljivo prate svoj napredak i proaktivno prilagođavaju svoje strategije učenja kada naiđu na prepreke (Rahimi i Cheraghi, 2024; Wilby, 2022; Zheng i sur., 2021). Taj je proces usko povezan s upotrebom metakognitivnih strategija i većom akademskom upornošću, što studentima pomaže svladati izazove i optimizirati ishode učenja. Stoga motivacija za učenje nije samo komplementarni faktor nego i kritična i snažna varijabla koja značajno utječe na učinkovitost učenja i akademska postignuća.

Hipoteza 7: Motivacija za učenje ima značajan pozitivan utjecaj na akademska postignuća.

Metodologija

Alati korišteni u analizi

Alati odabrani u ovome istraživanju su sveobuhvatna metaanaliza i AMOS (engl. *Analysis of Moment Structures*). Sveobuhvatna metaanaliza jest alat specifično izrađen za provedbu metaanaliza, a istraživačima nudi mnoge funkcije, kao što su izračun veličine učinka, izradu *šuma* grafova te analizu podgrupa (Wallace i sur., 2009; Almassri i Zaharudin, 2023). AMOS je računalni program za analizu modela strukturne jednadžbe, a koristi se za ispitivanje veza putanje među varijablama (Arbuckle i Wothke, 1999).

Kriteriji uključivanja

Primijenjeni su sljedeći kriteriji uključivanja za odabir literature koja će se istražiti pomoću metaanalize:

1. Predmet istraživanja mora biti utjecaj ili učinak učenja temeljenoga na suradnji čovjeka i stroja na studente.

2. Istraživanje mora imati eksperimentalni dizajn.

3. U istraživanju se izlažu detaljne i specifične statističke informacije o eksperimentalnim podatcima, kao što su veličina uzorka, srednja vrijednost i korelacija, koje su omogućile izračun odgovarajuće vrijednosti učinka istraživanja.

Proces odabira radova

Izvori u kojima su odabrani radovi objavljeni uključuju Web of Science (WoS), Scopus i EBSCO. Opsežno istraživanje provedeno je pomoću ključnih riječi „student" ili „čovjek" ili „stroj" ili „računalo" ili „robot" ili „umjetna inteligencija" ili „AI" i „suradničko učenje". Istraživanje je ograničeno na radove objavljene u razdoblju između siječnja 2013. godine i svibnja 2025. godine, napisane na engleskome jeziku te klasificirane kao „rad". Na kraju je za analizu odabrano 15 radova koji su bili temeljito pregledani. Eliminirani su radovi s nekontroliranim eksperimentima i izvješćima s nepotpunim podatcima. Proces analize literature prikazan je na Slici 1.

Slika 1

Pristranost u objavljivanju i procjena heterogenosti

Heterogenost uočena u veličinama učinka koje se u metaanalizi obrađuju može se pripisati varijacijama u nacrtu istraživanja, ispitanicima u eksperimentalnoj skupini te alatima mjerenja koji se spominju u literaturi korištenoj u analizi (Higgins i Thompson, 2002). Zbog toga je u ovome istraživanju proveden test heterogenosti. Razina heterogenosti u uzorku korištenome u metaanalizi određena je pomoću statističkoga postupka I^2 (s vrijednostima od 25 %, 50 % i 75 %, što odgovara niskoj, srednjoj i visokoj razini heterogenosti, za svaku vrijednost pojedinačno), statističkoga postupka Q te njihove značajnosti ($p < 0,05$) (Whitehead i Whitehead, 1991). Rezultati određivanja razine heterogenosti uzorka u metaanalizi pokazali su vrijednost statističkoga postupka Q od 112,682, što značajno nadilazi stupanj slobode ($df = 25$) i pokazuje statističku

značajnost ($p < 0,001$). Štoviše, vrijednost I^2 iznosila je 77,81 %, što prelazi prag od 75 % i upućuje na visoku razinu heterogenosti između uzoraka korištenih u metaanalizi. Zbog toga je u statističkoj analizi i daljnjoj procjeni istraživanja (Borenstein i sur., 2009) korišten model slučajnih učinaka kako bi se osigurala točnost i pouzdanost rezultata.

Rezultati

Procjena kvalitete

Procjena kvalitete literature uključene u postupak provedena je uz primjenu kriterija pri testiranju navedenih u Cochraneovu priručniku (Higgins i Green, 2008). Ti su kriteriji obuhvatili randomizaciju, prikriveno razvrstavanje, prikrivanje, potpunost podataka, selektivno izvještavanje o rezultatima te potencijalne druge vrste pristranosti. Rezultati procjene rizika od pristranosti u odabranih istraživanjima prikazani su na Slici 2. Utvrđeno je da je rizik od pristranosti u selektivnome izvještavanju bio nizak u svim istraživanjima te nije spomenuto da neki podatci nedostaju.

Slika 2

Test heterogenosti modela strukturne jednadžbe

Heterogenost je testirana primjenom I^2 statistike. Vrijednosti I^2 statistike za istraživanja uključena u analizu bile su relativno visoke, a njihove odgovarajuće p-vrijednosti bile su ispod 0,001 (vidi Tablicu 1), što upućuje na manjak homogenosti u vezama. Stoga je za izračun opće opterećenosti koeficijenata korelacije korišten model slučajnoga učinka. U ovome je istraživanju korištena Rosenthalova metoda koeficijenta gubitka sigurnosti (Rosenthal, 1986). Ako faktor gubitka sigurnosti prelazi prag od 5K + 10, može se utvrditi da ne postoji vidljiva pristranost. Stoga uzorci uključeni u ovo istraživanje gotovo da i nemaju interferenciju pristranosti. Tablica 1 također prikazuje detaljne parametre za svaku vezu, uključujući i koeficijente korelacije, intervale pouzdanosti i vrijednosti sigurnosnoga N.

Tablica 1

Rezultat testa korelacijskoga koeficijenta

U ovome su istraživanju ispitane ukupne korelacije između parova varijabli te je na temelju toga izrađena matrica korelacijskih koeficijenata prikazana u Tablici 2. Vrijednosti koje se nalaze izvan glavne dijagonale predstavljaju srednje korelacijske koeficijente opterećene prosječnom veličinom uzorka.

Tablica 2

Rezultati modela strukturne jednadžbe

U metaanalitičkoj korelacijskoj matrici veličine učinka izračunate su pomoću varirajućih veličina uzorka iz mnogobrojnih studija, dok metaanalitičko modeliranje strukturne jednadžbe obično zahtijeva analizu koja se provodi na temelju jedinstvene

veličine uzorka. Stoga, kako bi se ova razlika obrazložila i kako bi se potencijalna pristranost zbog velikih varijacija u veličini uzoraka svela na najmanju moguću mjeru, u ovome je istraživanju korištena harmonična srednja vrijednost veličine uzorka, što odgovara efektivnoj veličini uzorka od 833,123. Nakon toga je korelacijska matrica unesena u računalni program AMOS 24.0 koji je korišten za analizu modela strukturne jednadžbe, a u obzir su uzeti i koeficijenti pouzdanosti. Što se tiče konstrukata kod kojih pouzdanost nije navedena u izvornim istraživanjima, primijenjena je početna vrijednost pouzdanosti od 0,80, na temelju preporuka koje su dali Dalton i sur. (1998). Rezultati prikladnosti strukturnoga modela prikazani su u Tablici 3.

Tablica 3

Na temelju utvrđene matrice korelacijskih koeficijenata, u daljnjem je postupku korišten model strukturne jednadžbe kako bi se analizirala multivarijatna putanja veza između varijabli. Analiza putanje provedena je pomoću računalnoga programa AMOS 24.0, a strukturni model prikazan je na Slici 3. Kako se može vidjeti na slici, koeficijent putanje od lakoće korištenja k akademskim postignućima je 0,132. Koeficijent putanje od zadovoljstva do motivacije za učenje je 1,354, dok je koeficijent od zadovoljstva do akademskih postignuća 0,621. Nadalje, koeficijent putanje od motivacije za učenje do akademskih postignuća je 0,332.

Slika 3

Diskusija

Analiza je pokazala da je putanja od zadovoljstva do motivacije za učenje pokazala najjaču veličinu učinka ($\beta = 1,35$) te je snažno naglasila zadovoljstvo učenika kao najveći prediktor motivacijske angažiranosti koja slijedi. Ovaj je rezultat u skladu s rezultatima do kojih su došli Wang i sur. (2021), koji su utvrdili sličnu snažnu vezu u svojoj analizi virtualnih nastavnika u oblaku, a također se podudara i s rastućim brojem istraživanja koja naglašavaju ključnu ulogu afektivnih faktora učenika u nastavi na daljinu i nastavi koja se odvija uz pomoć tehnologije (Yalçınkaya, 2024). S teorijskoga aspekta, ova snažna veza uvelike podržava principe teorije samoodređenja (Ryan i Deci, 2000). Posebno podržava tvrdnju da pozitivna emocionalna iskustva i zadovoljstvo okružjem za učenje nisu samo periferne dobrobiti, nego su i ključne za ostvarivanje osnovnih psiholoških potreba učenika za autonomijom, kompetencijama i povezanošću, što u konačnici značajno povećava razinu intrinzične motivacije (Leon, 2018). U kontekstu učenja temeljenoga na suradnji čovjeka i stroja, zadovoljstvo učenika vjerojatno proizlazi iz percipirane suradnje koja se ostvaruje bez problema, pouzdanosti umjetne inteligencije te osjećaja ostvarenih postignuća pomoću nje, što sve zajedno pridonosi želji za učenjem.

Nadalje, motivacija za učenje potvrđena je kao izravan, pozitivan prediktor akademskih postignuća ($\beta = 0,33$), što je rezultat koji se podudara s velikim brojem ranije provedenih istraživanja u području obrazovanja (Chang, 2019; Chen i Tu, 2021; Meng i Hu, 2022).

Mehanizam koji leži u pozadini ove veze jednostavan je i razumljiv: motivirani učenici uglavnom pokazuju veću kognitivnu ustrajnost kada dođu u dodir sa zahtjevnim obrazovnim sadržajem, superiornu samoregulaciju pri upravljanju vlastitim procesom učenja te dosljednije ponašanje usmjereno na postizanje ciljeva. Ovi atributi izravno olakšavaju dublje razumijevanje nastavnoga sadržaja i učinkovitiju primjenu znanja, što su sve glavni čimbenici za ostvarivanje boljih akademskih postignuća (Sia i sur., 2024; Zhou i Zhang, 2024).

Posebno bitan rezultat modela je priroda veze između zadovoljstva i akademskih postignuća. Dok je koeficijent izravne putanja od zadovoljstva do akademskih postignuća sam po sebi relativno jak ($\beta = 0{,}62$), prisutnost značajnoga neizravnog utjecaja pomoću motivaciju za učenje ukazuje na djelomično posrednu vezu. To upućuje na zaključak da zadovoljstvo utječe na akademska postignuća putem mehanizma koji se sastoji od dvaju kanala: ima izravan učinak, koji možda nastaje smanjenjem anksioznosti zbog učenja i stvaranjem kognitivnoga stanja koje olakšava apsorpciju znanja, a ima i snažan neizravan utjecaj jer podržava intrinzičnu i ekstrinzičnu motivaciju učenika, što unaprjeđuje akademski trud i uspjeh. Ovo djelomično posredovanje ističe da, dok pozitivno zadovoljstvo može izravno dobro utjecati na postignuća, znatan dio njegova utjecaja kanalizira se kroz konstantnu energiju i motivaciju za učenje koju zadovoljstvo potiče.

Lakoća korištenja i korisnost prepoznati su kao središnji konstrukti modela prihvaćanja tehnologije (Davis, 1989). Međutim, rezultati ovoga istraživanja pokazuju da, u kontekstu učenja temeljenoga na suradnji čovjeka i stroja, ovi faktori imaju relativno ograničen izravan pozitivan učinak na akademska postignuća učenika. Ranija empirijska istraživanja pružila su slične dokaze koji potvrđuju ovu situaciju. Chen i sur. (2025) došli su do saznanja da lakoća korištenja nije značajno utjecala na motivaciju za učenje niti je pozitivno predvidjela akademska postignuća. Slično njima, Sarwar i sur. (2019) naveli su da lakoća korištenja nema značajan pozitivan učinak na suradničko učenje. Uz to, Nugroho i sur. (2018) pokazali su da ni korisnost ni lakoća korištenja nisu značajno predvidjeli akademska postignuća učenika. Kako su alati bazirani na umjetnoj inteligenciji postali uvelike standardizirani i lako ih je koristiti, lakoća korištenja i korisnost mogle bi postupno postati osnovna očekivana obilježja, a ne odlučujući faktori koji utječu na akademska postignuća (Dwivedi i sur., 2021). U takvim kontekstima ovi perceptualni konstrukti rjeđe izravno diferenciraju ishode učenja jer korisnici obično pretpostavljaju da su oni minimalno korisni i funkcionalni. Umjesto toga njihov se utjecaj može ostvariti neizravno pomoću drugih psiholoških i bihevioralnih mehanizama (Al-Emran i sur., 2018). Lakoća korištenja i korisnost trebali bi se redefinirati kao temeljni uvjeti u inteligentnom okružju za učenje, umjesto da ih se smatra izravnim prediktorima akademskih postignuća učenika.

Općenito gledajući, ovakvi rezultati modeliranja strukturne jednadžbe pružaju uvid u dinamični i sinergijski odnos između sustava tehnološke podrške – „stroja“ u učenju temeljenom na suradnji čovjeka i stroja – i unutarnjih psiholoških faktora učenika u

zajedničkom oblikovanju akademskoga uspjeha. Vrijednost tehnoloških alata nije samo funkcionalna nego i psihološka, a očituje se u putanjama zadovoljstva i motivacije (Nguyen i sur., 2019). Zbog toga se u ovome istraživanju tvrdi da buduća istraživanja, instrukcijski dizajn i evaluacija obrazovnih tehnologija moraju izaći izvan granica čiste procjene funkcionalnosti. Postoji velika potreba za dubljom i namjernom integracijom stvaranja pozitivnih emocionalnih iskustava i podrške motivacijskih procesa u samu srž razvoja obrazovne tehnologije (Wang i sur., 2022).

Kako bi se u potpunosti iskoristio potencijal tehnologije, obrazovni djelatnici i osobe koje rade na razvoju tehnologije moraju osmisliti okružja za učenje temeljenih na suradnji čovjeka i stroja koja nisu samo učinkovita, nego pružaju zadovoljstvo i potiču motivaciju učenika. Hibridno učenje imalo je pozitivan utjecaj na proces učenja učenika (Rasheed i sur., 2020). Integracija hibridnoga učenja u okružja za učenje temeljena na suradnji čovjeka i stroja omogućava nastavnicima personaliziranu nastavu i pruža ciljanu povratnu informaciju tako što putem *online* platformi prati postignuća učenika u stvarnome vremenu. Ovakav pristup stvara iskustvo učenja u kojemu je učenik jako angažiran, a sve to povećava njegov interes i motivaciju (Suryono i sur., 2023; Ustun i sur., 2023). S druge strane, učenje u grupama, koje je ključno obilježje učenja temeljenoga na suradnji čovjeka i stroja, naglašava važnost suradničkoga učenja u izgradnji i dijeljenju znanja. Učenjem u grupama učenici mogu izmijeniti različite perspektive, iskustva i strategije, što obogaćuje njihovo razumijevanje nastavnoga gradiva i olakšava dubinsko učenje. Zadatci za učenje također bi trebali biti osmišljeni tako da potiču razmišljanje, analizu i rješavanje problema (Sabo Junger i sur., 2024). Kreiranjem scenarija s primjerima problemskoga učenja nastavnici mogu stimulirati pozitivne emocije učenika (Saygili Yildirim i Sahin Izmirli, 2024). Obrazovni bi djelatnici trebali pojačati svoje napore i istražiti potencijal hibridnoga i grupnoga učenja u praksi učenja temeljenoga na suradnji čovjeka i stroja te nastaviti unaprjeđivati svoj instrukcijski dizajn. Nastavnici bi trebali povećati razinu svoje tehnološke pismenosti i u skladu s time koristiti računalne tehnologije (Miljković Krecar i Pavlin-Bernardić, 2025). *Chatbotovi*, platforme za *online* učenje te suradnički sustavi su svi važni faktori koji olakšavaju proces učenja učenika. Posljednjih je godina upotreba *chatbotova* u okružjima za *online* učenje postala iznimno velika, služeći kao inteligentan program koji može simulirati dijalog između ljudi (Kuhail i sur., 2023). Kao prvo, *chatbotovi* pružaju podršku u stvarnom vremenu i personalizirane odgovore kako bi učenicima pomogli svladati prepreke u učenju te tako povećavaju učinkovitost procesa učenja. Kao drugo, koristeći tehnologiju obrade prirodnoga jezika, *chatbotovi* se uključuju u interaktivne dijaloge s učenicima tako da iskustvu učenja dodaju živopisnost i interaktivnost (Kasthuri i Balaji, 2023). Takva interaktivnost doprinosi povećanom interesu i sudjelovanju učenika u procesu učenja, stvarajući upečatljivo iskustvo učenja. Algoritmi umjetne inteligencije mogu se koristiti za predviđanje stope napuštanja školovanja među učenicima i za pružanje podrške kontinuiranom učenju (Spalević i sur., 2025). Obrazovni djelatnici te tehnologije mogu strateški integrirati kako bi povećali uključenost učenika tijekom procesa učenja (Viberg i sur., 2023).

Ovo istraživanje daje mogući smjer budućim istraživanjima o učenju temeljenom na suradnji čovjeka i stroja te ispituje učinkovitost učenja temeljenoga na suradnji čovjeka i stroja u nastavnoj praksi, naglašavajući važnost tehničkih i emocionalnih faktora u poticanju motivacije za učenje među učenicima i krajnjeag akademskog uspjeha. Očekuje se da će ovo istraživanje pružiti vrijedne smjernice te služiti kao referenca za istraživače koji se bave ispitivanjem i odabirom tema za istraživanje povezanih s učenjem temeljenom na suradnji čovjeka i stroja.

Potrebno je naglasiti i ograničenja ovoga istraživanja. Kriteriji uključenosti bili su ograničeni na radove s potpunim izvješćima, a isključena su bila istraživanja koja su sadržavala samo sažetke ili osnovne detalje. Uz to, analiza je ograničena na radove napisane na engleskome jeziku. Tijekom procesa modeliranja strukturnih jednadžbi u nekim istraživanjima nije bilo jamstva da su podatci potpuno pouzdani. U budućim bi se istraživanjima trebao uključiti širi raspon moderirajućih varijabli i provesti detaljna ispitivanja kako bi se produbilo naše razumijevanje o njihovom učinku. Istraživače bi se trebalo potaknuti da se uključe u višejezična istraživanja literature i provedu širu analizu s ciljem detaljnoga razumijevanja učenja temeljenoga na suradnji čovjeka i stroja.

Zaključak

Rezultati ovoga istraživanja imaju značajne implikacije za istraživanja i praksu. U istraživanju su korištene metode metaanalitičkoga modeliranja strukturne jednadžbe kako bi se detaljno istražila postojeća literatura o učenju temeljenom na suradnji čovjeka i stroja, s ciljem stjecanja boljega uvida u faktore koji utječu na učenje temeljeno na suradnji čovjeka i stroja. Analiza literature provedena je na radovima napisanima između 2013. i 2025. godine dostupnima na bazama podataka Web of Science, Scopus i EBSCO. Odabrano je 15 radova za izradu modela strukturne jednadžbe. Rezultati modeliranja strukturnih jednadžbi otkrili su nekoliko značajnih putanja između ključnih varijabli. Model je prepoznao zadovoljstvo kao primarni faktor koji ima snažan utjecaj i na motivaciju za učenje i na akademska postignuća. Istovremeno je potvrđena uloga motivacije za učenje kao snažnoga pozitivnog utjecaja na akademska postignuća. Metaanalitičko modeliranje strukturne jednadžbe oslanja se na sustavnu sintezu korelacijskih matrica spomenutih u ranijim empirijskim istraživanjima, koje služe kao osnovna ulazna vrijednost za procjenu strukturnih veza na metaanalitičkoj razini. Buduća bi istraživanja trebala uključiti veći broj empirijskih istraživanja, primijeniti strože metode dijagnosticiranja pristranosti te ispitati longitudinalne i eksperimentalne dizajne za daljnju validaciju rezultata.