EXAMINING THE IMPACT OF RESOURCE MANAGEMENT, SELF-EFFICACY, AND MOTIVATION ON DEEP LEARNING IN A VIRTUAL LEARNING ENVIRONMENT: A PLS-SEM APPROACH

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Abstract

This study explores the impact of resource management and motivation on deep learning outcomes within virtual learning environments among students from Technical and Vocational Education and Training (TVET) institutions in Kenya. Effective resource management and motivation are crucial factors that influence educational success, and understanding their effects on deep learning can enhance educational practices. Data was collected from 487 students through a structured survey administered via Survey Monkey, with a preliminary pilot test conducted to ensure the survey‘s clarity. The analysis involved exploratory factor analysis and Partial Least Squares structural equation modeling (PLS-SEM). The findings indicate that effective resource management has a significant positive impact on deep learning outcomes and student motivation. Specifically, motivation and resource management were both found to significantly affect deep learning, with motivation exhibiting the strongest direct influence. Resource management also positively impacts self-efficacy, which subsequently enhances deep learning. The model explained a substantial portion of the variance in deep learning, highlighting the complex interplay between these factors. Based on these results, it is recommended that educators focus on improving resource management by providing diverse and accessible learning tools and support systems. Additionally, motivational strategies should be implemented to engage students and foster their intrinsic interest in learning. Also, by integrating these findings into virtual learning frameworks, educational institutions can create environments that better support deep learning and improve student performance. Future research should consider exploring additional factors that influence deep learning and evaluating the effectiveness of specific resource management practices in various educational contexts.

Keywords*:* Resource Management, Motivation, Deep Learning, VLE

Introduction

Virtual learning environments (VLEs) have evolved dramatically, integrating deep learning methodologies that extend beyond traditional rote memorization (Segooa & Kalema, 2015; Sølvik & Glenna, 2021). These digital platforms incorporate multimedia, interactive simulations, and online assessments to enhance student engagement and personalized learning. Despite these advancements, the mechanisms through which strategic resource management in VLEs impacts deep learning remain underexplored. This approach encourages students to explore topics in-depth, connect concepts, and synthesize information (Ramsden, 1979). It fosters inquiry-based learning, critical thinking, and problem-solving by integrating knowledge from multiple disciplines (Richardson & Newby, 2006). Collaborative learning in VLEs further enriches this process by promoting diverse perspectives and group problem-solving (Bharathi & Pande, 2024), ultimately preparing students for both academic and professional challenges (Biggs, 1988).

Effective resource management is pivotal for optimizing deep learning in VLEs. Key elements include time management, study environment management, and effort regulation. Time management involves structuring study schedules to meet deadlines and reduce procrastination,enhancing engagement and productivity (Wu, 2023). A well-managed study environment–quiet, well-lit, and free from distractions–supports sustained attention and motivation (Rashid & Asghar, 2016). Effort regulation, including goal-setting and persistence, boosts self-efficacy and learning outcomes (Prifti, 2020).

Motivation and self-efficacy are crucial for deep learning outcomes in VLEs (Chasetareh et al., 2022). Motivation drives active participation and perseverance, while self-efficacy enhances students' confidence in tackling complex problems and engaging deeply in learning activities (Hatlevik et al., 2018; Macalisang & Bonghawan, 2024). Therefore, these factors create a positive feedback loop that fosters critical thinking and lifelong learning.

This research aims to investigated how resource management (time, study environment, effort), motivation, and self-efficacy predict deep learning in VLEs. It will also explore how motivation mediates the relationship between resource management and deep learning, offering insights for improving educational strategies in virtual settings.

Literature Review

Deep Learning

Deep learning has revolutionized education by shifting from basic knowledge acquisition to transformative learning experiences (Esteban-Guitart & Gee, 2020). Unlike traditional surface learning, which emphasizes rote memorization and basic comprehension, deep learning encourages students to critically analyze, synthesize, and apply knowledge meaningfully (Wang & Zhang, 2018; Richardson et al., 2012). This approach enhances academic performance and cultivates essential skills for success in today‘s world (Duff, 2004; Richardson et al., 2012; Wilding & Andrews, 2006).

Deep learning promotes cognitive engagement that goes beyond mere factual understanding. Students are encouraged to delve deeply into subjects, exploring fundamental concepts and their implications. This profound engagement helps build robust mental models that integrate new information with existing knowledge (Aharony, 2006). Additionally, tackling complex ideas fosters flexible thinking and adaptive problem-solving (Jiang, 2022).

One of the key benefits of deep learning is its focus on critical thinking and problem-solving (Jiang, 2022). Students learn to question assumptions, evaluate evidence, and construct reasoned arguments (Wang & Zhang, 2018). In today‘s rapidly changing world, these skills are crucial for making informed decisions and driving innovation (Núñez & León, 2016). Deep learning also fosters creativity and innovation by encouraging students to explore diverse perspectives and experiment with solutions (Núñez & León, 2016; Zhao & Qin, 2021; Sølvik& Glenna, 2021).

In virtual learning environments, where physical separation can limit interaction, deep learning is essential for effective communication and collaboration (Lindblom-Ylänne& Lonka, 1998). Collaborative projects and online discussions help students refine their interpersonal skills, articulate ideas clearly, and work towards shared goals, preparing them for teamwork in diverse global contexts.

Resource Management and Deep Learning in Virtual Learning Environments

Resource management in virtual learning environments is crucial for facilitating deep learning. It involves the strategic allocation and optimization of educational resources to support engagement, critical thinking, and comprehensive understanding. Effective planning and organization of study schedules help students engage deeply with course materials without feeling overwhelmed (Claessens et al., 2007; List &Nadasen, 2016). Setting clear timelines and breaking tasks into manageable chunks aids in prioritizing work, meeting deadlines, and allocating time for reflection (Zhu et al., 2020). Creating an optimal physical and psychological learning space enhances concentration and focus. A well-organized environment, free from distractions, supports active participation in virtual learning activities (Rashid & Asghar, 2016). This involves setting realistic goals, monitoring progress, and maintaining motivation despite challenges. Effective effort regulation encourages persistence and fosters a deeper understanding of the subject matter (Prifti, 2020).

Technological tools such as learning management systems, multimedia content, and virtual collaboration platforms are integral to virtual learning environments (Marshall & Sankey, 2023; Bradley, 2020). Effective resource management ensures these tools are selected and integrated thoughtfully. Interactive simulations and virtual labs, for example, enable students to engage actively with complex concepts (Pannekoek & Ally, 2008).

Resource management also includes selecting diverse instructional materials tailored to students' needs. Digital textbooks, video lectures, and open educational resources (OERs) offer flexibility and accessibility, supporting deep learning by catering to various learning styles (Orr et al., 2015; Prameswaro et al., 2023). Human support systems, such as instructor guidance and academic advising, further enhance deep learning by providing personalized feedback and fostering a supportive learning community (Coll et al., 2014; McGill et al., 2020). Given these findings, it is reasonable to hypothesize:

Hypothesis 1: Resource management positively predicts deep learning in virtual learning environments.

Motivation

Motivation is crucial for academic success in virtual learning environments. It drives learners to pursue goals and shapes attitudes and behaviors toward learning (Hsiao, 2021). Motivation can be intrinsic or extrinsic, this involves personal interest and satisfaction in learning. Intrinsically motivated students engage deeply with the material, exhibit perseverance, and show higher cognitive engagement (Legault, 2016; Oudeyer& Kaplan, 2007; Rojo, 2015). Driven by external rewards and recognition, extrinsic motivation includes achieving high scores or receiving praise (Bear et al., 2017). While effective for initial engagement, extrinsic motivation must be aligned with intrinsic motivators to sustain deep learning (Bear et al., 2017; Fırat et al., 2017). In virtual learning environments, where students manage their learning independently, fostering both intrinsic and extrinsic motivation is crucial (Hartnett, 2016; Everaert et al., 2017). Designing engaging content, providing opportunities for autonomous learning, and incorporating elements of extrinsic motivation like clear expectations and feedback can enhance motivation (Zou et al., 2023). Research shows a positive link between motivation and deep learning, characterized by cognitive comprehension and application (An et al., 2023; Aguilar et al., 2021; Vansteenkiste et al., 2020). Effective resource management also supports motivation by reducing feelings of overwhelm and enhancing the use of learning materials (Rani et al., 2023; Harackiewicz et al., 2016). Therefore, based on these insights, the following hypotheses are formulated:

Hypothesis 2: Resource management positively predicts motivation in virtual learning environments.

Hypothesis 3: Motivation positively predicts deep learning in virtual learning environments.

Self-Efficacy

Self-efficacy, representing the determination to pursue and complete educational goals, is vital for academic success, especially in virtual learning environments (Hartnett, 2016). It influences students' engagement, resilience, and commitment to learning (Shen et al., 2013).

High self-efficacy is strongly correlated with deep learning, as it drives students to invest time and effort in mastering complex material (Kim et al., 2022; Cheng, 2021). Self-efficacy is also linked to motivation and resource management. Motivated students are more likely to persevere and seek help (Fırat et al., 2018), while effective resource management enhances self-efficacy by helping students handle challenges and stay engaged (Dabbagh &Kitsantas, 2012). Moreover, the relationship between learning persistence and deep learning is bidirectional. Engaging deeply with material enhances self-efficacy by providing a sense of accomplishment (Chen et al., 2020). Given these insights, the following hypotheses are formulated:

Hypothesis 4: Resource management positively predicts self-efficacy in virtual learning environments.

Hypothesis 5: Self-efficacy positively predicts deep learning in virtual learning environments.

Hypothesis 6: Motivation positively predicts self-efficacy in virtual learning environments.

The Mediated Effect of Self-Efficacy and Motivation

In virtual learning environments, the interplay between resource management, self-efficacy, motivation, and deep learning is complex. Effective resource management enhances self-efficacy by providing control and confidence, leading to increased engagement in deep learning (Zimmerman, 1990; Shen et al., 2013). Self-efficacy also boosts motivation, leading to deeper engagement and critical thinking (Chen et al., 2020). Motivation supports the relationship between resource management and deep learning. Efficient resource management supports intrinsic motivation and aligns with students' goals, while extrinsic motivators provide additional incentives (Legault, 2016; Bear et al., 2017). Self-efficacy and motivation together create a feedback loop where resource management enhances both, driving deep learning (Fırat et al., 2018). Based on these insights, the following hypothesis is formulated

Hypothesis 7: Self-efficacy mediates the relationship between resource management and deep learning in virtual learning environments.

Research Methodology

Participants

The study involved 487 students enrolled in virtual learning programs across seven TVET institutions in Kenya. The gender distribution of the sample comprised 275 male students (56.5%) and 212 female students (43.5%). In terms of program enrollment, 289 students (59.3%) were enrolled in diploma programs, while 198 students (40.7%) were pursuing certificate programs. The academic level of the participants included 162 first-year students (33.3%), 175 second-year students (36.0%), and 150 third-year students (30.8%). The inclusion criteria ensured that participants had experience with virtual learning environments, making them well-suited to provide insights into the impact of resource management, self-efficacy, and motivation on deep learning.

Instruments

The data for this study was collected using a structured survey designed to measure the key constructs of resource management, self-efficacy, motivation, and deep learning. The survey comprised multiple sections, each targeting a specific construct relevant to the study. The resource management construct included items adapted from validated scales on resource management in educational contexts, particularly the Motivated Strategies for Learning Questionnaire (Lee et al., 2020). This instrument assessed students' ability to manage their study time, utilize learning materials effectively, seek help when needed, organize their study environment, set clear goals, and adapt study strategies based on learning progress.

Self-Efficacy Items were adapted from Zhao and Liu (2022) and originally based on Sherer et al. (1982) scale. These items were tailored to measure students' confidence in managing learning tasks, overcoming challenges in virtual learning environments, performing well on assignments, managing time effectively, and learning independently. The motivation instrument incorporated items adapted from the revised two-factor Study Process Questionnaire (Biggs et al., 2001). It included items to capture intrinsic motivation (personal interest and satisfaction in learning) and extrinsic motivation (desire for good grades and satisfaction from mastering challenging tasks). Finally, the deep learning section included items from a five-item Deep Learning Scale designed by Zhao and Liu (2022). This scale was formulated to assess students' engagement with course material, critical thinking skills, application of knowledge to new contexts, exploration of different perspectives, and depth of understanding in the course content.

Data Collection

The data collection for this study was executed via SurveyMonkey, an online survey tool that enabled efficient distribution and response gathering. Participants were emailed a survey link along with detailed instructions for completion. The survey was designed to be user-friendly and accessible, which led to a high response rate and reliable data. Participants were given a two-week window in August 2023 to complete the survey, with periodic reminders sent to enhance participation. The initial target population comprised 870 students enrolled in virtual learning programs across seven TVET institutions in Kenya, with 487 responses ultimately collected.

Prior to the main data collection, an initial pilot test was conducted with 42 students to verify the quality and suitability of the survey. This pilot test aimed to assess the clarity, comprehensibility, and relevance of the questionnaire for the target population. Pilot participants provided feedback on the clarity of instructions, the relevance of the items, and any difficulties they faced while responding. Based on this feedback, necessary revisions and adjustments were made to improve the questionnaire. The reliability analysis of the pilot test data showed favorable results for all measured constructs in the study. Specifically, the internal consistency was high for motivation (Cronbach‘s $\alpha = 0.754$), self-efficacy (Cronbach‘s $\alpha = 0.813$), resource management (Cronbach‘s $\alpha = 0.745$), and deep learning (Cronbach‘s $\alpha = 0.854$). These results indicated that the survey items were reliable and appropriate for measuring the intended constructs.

In addition, before administering the questionnaires, participants were informed about the research objectives and assured that their responses would remain confidential. They were also told they could withdraw from the study at any time without any repercussions. All participants provided voluntary consent to participate in the study. Throughout the data collection process, the researchers strictly adhered to ethical standards to maintain the integrity and confidentiality of the data. This rigorous approach to data collection ensured the study's findings would be both reliable and valid.

Data Analysis

Prior to conducting statistical analyses, extensive preprocessing procedures were conducted. These included checks for outliers and missing values, as well as assessments for normality and common method bias using Harman's single-factor test (Aguirre-Urreta & Hu, 2019). Exploratory factor analysis was employed to determine whether any single dominant factor influenced the variance in the dataset. Initial assessments confirmed the sample's adequacy with a Kaiser-Meyer-Olkin Measure of Sampling Adequacy of 0.895, further supported by Bartlett's Test of Sphericity ($\chi2 = 4193.448$, df = 190, $p < 0.001$), indicating strong inter-item correlations suitable for factor analysis.Principal Axis Factoring was then utilized to explore the variance explained by the extracted factors(Baumgartner & Homburg, 2023). The first four factors collectively accounted for 63.074% of the variance. Factor 1 had an initial eigenvalue of 6.053, explaining 30.264% of the variance (28.040% after extraction and 3.954% after rotation). Factor 2 explained 12.567% initially (10.271% after extraction and 3.841% after rotation) with an eigenvalue of 2.513. Factor 3 explained 11.112% initially (8.913% after extraction and 3.692% after rotation) with an eigenvalue of 2.222, while Factor 4 explained 9.130% initially (6.964% after extraction and 3.430% after rotation) with an eigenvalue of 1.826. These findings collectively indicated that no single factor dominated, thereby alleviating concerns regarding common method bias (See Figure 1).

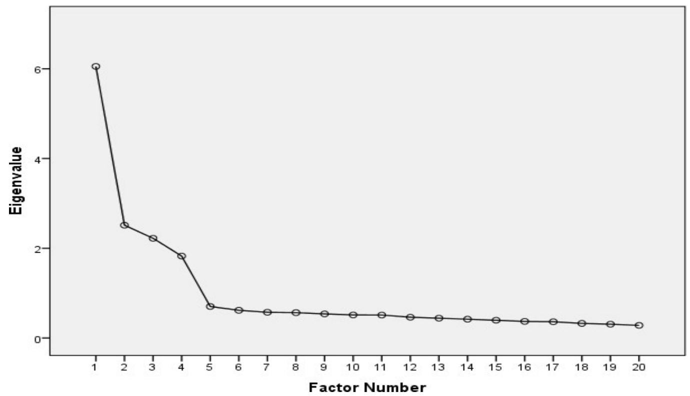

Figure1: Scree plot showing the eigenvalues of factors extracted from Principal Axis Factoring

Further, to assess the reliability and validity of the questionnaires, Cronbach's alpha, composite reliability (rho_a and rho_c), and average variance extracted (AVE) were calculated(Hair et al., 2014). Discriminant validity was confirmed using the Fornell-Larcker criterion(Henseler et al., 2014). Collinearity among predictors was evaluated using Variance Inflation Factors (VIF)(Vörösmarty & Dobos, 2020). Subsequently, Structural Equation Modeling (SEM) was performed using Partial Least Squares in SMARTPLS version 4.0 to test the hypothesized model(Sarstedt et al., 2021; Hair et al., 2014). Additionally, fsQCA version 4.1 facilitated Qualitative Comparative Analysis (QCA) to explore different configurations influencing the outcomes(Kumar et al., 2022).

Results Analysis

Measurement Model Analysis

The measurement model underwent symmetrical analysis to assess the reliability and validity of its constructs. The reliability and validity of each construct were rigorously evaluated (See Table 1). Deep Learning exhibited strong internal consistency with a Cronbach's alpha (**α=**0.845), supported by high composite reliability measures (rho_a = 0.850, rho_c = 0.890) and an average variance extracted (AVE) of 0.618, indicating reliable and convergent measurement. Similarly, Motivation showed robust reliability with a Cronbach's alpha (**α=** 0.827), complemented by strong composite reliability (rho_a = 0.849, rho_c = 0.885) and an AVE of 0.659. Resource Management demonstrated excellent internal consistency (Cronbach's alpha α = 0.863), with high composite reliability (rho_a = 0.872, rho_c = 0.898) and an AVE of 0.594, confirming reliability and convergent validity. Self-Efficacy also exhibited strong internal consistency (Cronbach's alpha **α** = 0.866), supported by high composite reliability (rho_a = 0.871, rho_c = 0.903) and an AVE of 0.651, indicating reliable and convergent measurement.

In addition, Outer loadings were examined to assess the strength of relationships between observed indicators and their respective latent constructs in the measurement model. For Deep Learning, indicators DPL1 to DPL5 exhibited strong loadings ranging from 0.725 to 0.852, indicating robust measurement of this construct. Motivation indicators (MOT1 to MOT4) showed substantial loadings ranging from 0.738 to 0.893, confirming reliable measurement of motivational factors. Resource Management indicators (RMT1 to RMT6) demonstrated consistent loadings ranging from 0.707 to 0.841, reflecting solid measurement of resource management behaviors. Self-Efficacy indicators (SE1 to SE5) displayed strong loadings ranging from 0.780 to 0.854, indicating reliable measurement of self-efficacy beliefs.

Table 1
Reliability and ValidityMeasures of Constructs in the MeasurementModel

		Outer loadings	Cronbach alpha (α)	CR (rho_a)	CR (rho_c)	AVE
Deep Learning	DPL1	0.779	0.845	0.850	0.890	0.618
	DPL2	0.799				
	DPL3	0.771				
	DPL4	0.852				
	DPL5	0.725				
Motivation	MOT1	0.893	0.827	0.849	0.885	0.659
	MOT2	0.738				
	MOT3	0.799				
	MOT4	0.811				
Resource management	RMT1	0.707	0.863	0.872	0.898	0.594
	RMT2	0.736				
	RMT3	0.735				
	RMT4	0.817				
	RMT5	0.841				
	RMT6	0.780				
Self-efficacy	SE1	0.819	0.866	0.871	0.903	0.651
	SE2	0.788				
	SE3	0.854				
	SE4	0.791				
	SE5	0.780				

Table 2
Assessment of DiscriminantValidity using the Fornell-Larcker Criterion

	Deep Learning	Motivation	Resource Management	Self-Efficacy
Deep Learning	**0.786**			
Motivation	0.352	**0.812**		
Resource Management	0.280	0.294	**0.771**	
Self-Efficacy	0.311	0.327	0.299	**0.807**

Note: "Values highlighted in bold on the diagonal represent the square root of the Average Variance Extracted (AVE)

Discriminant validity was established through the Fornell-Larcker criterion. Deep Learning, Motivation, Resource Management, and Self-Efficacy all demonstrated higher AVE values compared to their correlations with other constructs, confirming their distinctiveness in the measurement model (See Table 2). Assessment of collinearity using VIF indicated no issues of multicollinearity among predictor variables, with all VIF values below 2.5 (see Table 3).

Table 3
Collinearity Statistics for Indicators in the Measurement Model

Items	VIF
DPL-1: I critically analyze the information presented in this course.	1.753
DPL-2: I reflect on how the course material connects to real-world situations.	1.864
DPL-3: I explore different perspectives on topics covered in this course.	1.686
DPL-4: I apply what I learn to solve problems beyond what is covered in the course.	2.179
DPL-5: I engage deeply with the course content to understand its underlying principles.	1.548
MOT-1: I am genuinely interested in the topics covered in this course.	2.349
MOT-2: I enjoy the process of learning new information and skills.	1.525
MOT-3: Getting good grades in this course is important to me.	1.693
MOT-4: I find satisfaction in mastering challenging tasks and assignments.	1.877
RMT-1: I manage my study time effectively.	1.529
RMT-2: I use learning materials efficiently to support my studies.	1.660
RMT-3: I seek help from instructors or peers when I encounter difficulties.	1.676
RMT-4: I organize my study environment to minimize distractions.	2.056
RMT-5: I set clear goals for my study sessions.	2.212
RMT-6: I adapt my study strategies based on my learning progress	1.846
SE-1: I am confident in my ability to understand complex concepts in this course.	1.908
SE-2: I believe I can overcome challenges that arise in my virtual learning environment.	1.833
SE-3: I am sure I can perform well on tasks and assignments in this course.	2.329
SE-4: I can effectively manage my time to meet the demands of this course.	1.863
SE-5: I feel capable of learning independently in this virtual learning environment.	1.775

Structural Analysis

The overall model fit was evaluated using multiple indices, revealing how well the model represented the data. The Standardized Root Mean Square Residual (SRMR) values were 0.045 for the saturated model and 0.060 for the estimated model, indicating a good fit. The Unweighted Least Squares Discrepancy (d_ULS) values were 0.061 for the saturated model and 0.001 for the estimated model, showing that the estimated model had an exceptionally good fit. The Geodesic Discrepancy (d_G) values were 0.062 for the saturated model and 0.018 for the estimated model. The chi-square ($\chi 2=$) values were 461.541 for the saturated model and 485.729 for the estimated model. The Normed Fit Index (NFI) values were 0.994 for the saturated model and 0.989 for the estimated model, both demonstrating a good fit to the data.The R^2 values were used to indicate the proportion of variance explained by the model for each endogenous construct. For Deep Learning, the model explained 19.2% of the variance ($R^2 = 0.192$), indicating a substantial portion of variance accounted for by the predictors. Motivation had an R^2 of 0.107, suggesting that the predictors explained approximately 10.7% of the variance in this construct. Self-Efficacy had an R^2 of 0.090, indicating that the model explained 9% of the variance in Self-Efficacy, which reflects moderate explanatory power.

Table 4
Path Analysis Results Including Direct and Indirect Effects

Path relationship	Path coefficients	T-values	P values	Confidence interval 2.5%	Confidence interval 97.5%
Age → Deep Learning	0.000	0.001	0.999	-0.084	0.082
Course → Deep Learning	0.058	1.414	0.157	-0.023	0.139
Gender→ Deep Learning	0.093	1.113	0.266	-0.073	0.251
Motivation → Deep Learning	0.240	5.666	0.000	0.158	0.323
Resource Management → Deep Learning	0.142	2.991	0.003	0.051	0.235
Resource Management → Self Efficacy	0.299	6.991	0.000	0.214	0.385
Self-Efficacy→ Deep Learning	0.183	3.941	0.000	0.093	0.274
Self-Efficacy → Motivation	0.327	7.707	0.000	0.243	0.409
Resource Management → Self Efficacy → Deep Learning	0.055	3.294	0.001	0.026	0.091
Resource Management → Self Efficacy → Motivation→ Deep Learning	0.023	3.413	0.001	0.013	0.040
Resource Management → Self Efficacy → Motivation	0.098	4.453	0.000	0.059	0.145
Self-Efficacy → Motivation→ Deep Learning	0.078	4.511	0.000	0.048	0.116

The structural model analysis revealed several significant relationships among the constructs, as illustrated in Table 4 and Figure 2. The analysis showed that age and gender did not significantly impact deep learning. However, Motivation had a significant positive effect on Deep Learning (path coefficient = 0.240, t = 5.666, $p < 0.001$, 95% CI: 0.158 to 0.323), indicating a strong influence. Resource Management also had a positive impact on Deep Learning (path coefficient = 0.142, t = 2.991, p = 0.01, 95% CI: 0.051 to 0.235). Additionally, Resource Management significantly influenced Self-Efficacy (path coefficient = 0.299, t = 6.991, $p < 0.001$, 95% CI: 0.214 to 0.385). Self-Efficacy significantly predicted Deep Learning (path coefficient = 0.183, t = 3.941, $p < 0.001$, 95% CI: 0.093 to 0.274). Moreover, Self-Efficacy had a substantial positive effect on Motivation (path coefficient = 0.327, t = 7.707, $p < 0.001$, 95% CI: 0.243 to 0.409).

Indirect effects were also observed. The indirect effect of Resource Management on Deep Learning through Self-Efficacy was significant (path coefficient = 0.055, t = 3.294, $p < 0.01$, 95% CI: 0.026 to 0.091). Additionally, the sequential mediation of Resource Management to Deep Learning via Self-Efficacy and Motivation was significant (path coefficient = 0.023, t = 3.413, $p < 0.01$, 95% CI: 0.013 to 0.040). The path from Resource Management to Motivation through Self-Efficacy was significant (path coefficient = 0.098, t = 4.453, $p < 0.001$, 95% CI: 0.059 to 0.145). Lastly, the indirect effect of Self-Efficacy on Deep Learning through Motivation was also significant (path coefficient = 0.078, t = 4.511, $p < 0.001$, 95% CI: 0.048 to 0.116).

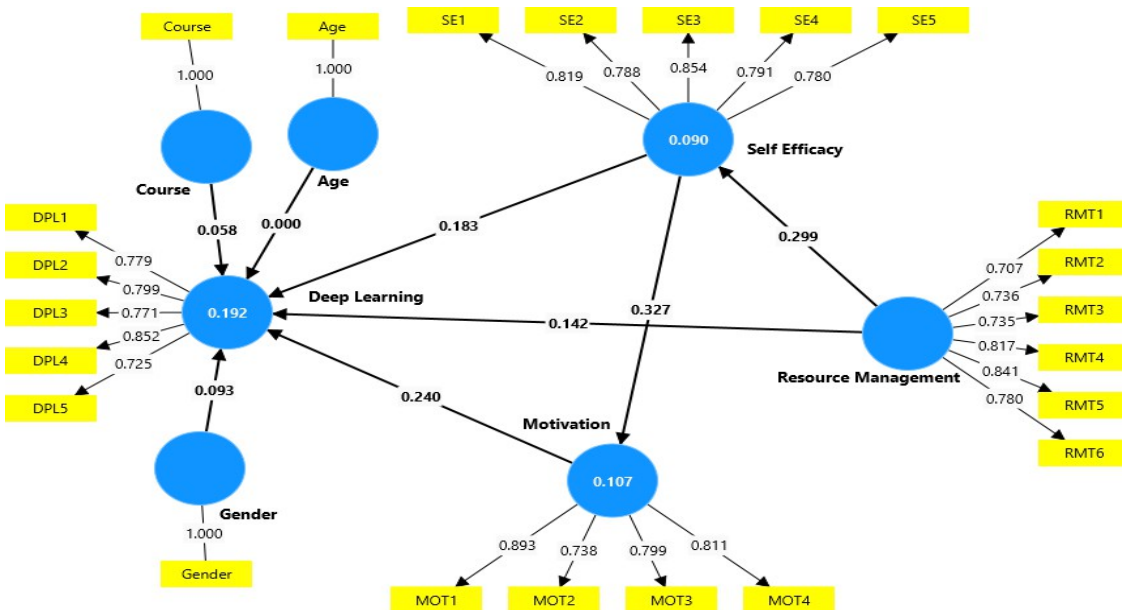

Figure 2: Structural Model Analysis

Study Discussion

This study highlights the significant role of effective resource management in enhancing deep learning outcomes within virtual learning environments (VLEs). Our findings support Hypothesis 1, indicating that strategic allocation and utilization of educational resources, such as multimedia tools and collaborative platforms, positively influence deep learning engagement. By providing diverse learning tools, educators facilitate students' ability to explore topics comprehensively, synthesize information, and apply knowledge creatively (Esteban-Guitart & Gee, 2020; Wang & Zhang, 2018). Moreover, our results validate Hypothesis 2, demonstrating that effective resource management also positively impacts students' motivation. Ensuring accessibility, usability, and support systems creates a conducive learning environment where students are empowered to engage actively with course materials and pursue their learning goals autonomously (Hsiao, 2021; Fırat et al., 2018). This alignment between resource availability and motivational factors enhances students' persistence and enthusiasm, which contributes to deeper learning experiences (Chasetareh et al., 2022).

In addition, Hypothesis 3 is confirmed, showing that motivation significantly predicts deep learning. Motivated students exhibit higher cognitive engagement, connecting ideas and applying knowledge critically (An et al., 2023; Aguilar et al., 2021). This intrinsic motivation fosters an environment where students actively seek to understand complex concepts and solve problems creatively, essential for both academic and professional success (Ito & Umemoto, 2023; Tang et al., 2023). Our study also supports Hypothesis 4, indicating that effective resource management positively influences students' self-efficacy in VLEs. Structured learning experiences and clear expectations empower students to navigate academic challenges independently and develop confidence in their abilities (Shen et al., 2013; Dabbagh &Kitsantas, 2012). This self-efficacy is crucial for sustaining engagement and persistence in deep learning activities (Chen et al., 2020). Furthermore, Hypothesis 5 is validated, as our findings demonstrate that students' self-efficacy positively predicts their engagement in deep learning processes. Students who believe in their ability to master challenging tasks are more likely to invest time and effort in understanding complex concepts, thereby improving their learning outcomes (Kim et al., 2022; Cheng, 2021). Our study also confirms Hypothesis 6, highlighting the reciprocal relationship between motivation and self-efficacy. Motivated students set ambitious goals, persist through challenges, and actively seek growth opportunities, which enhances their overall self-efficacy (Everaert et al., 2017; Zou et al., 2023). Conversely, higher self-efficacy helps students maintain motivation by viewing academic challenges as opportunities for learning and personal development (Shroff et al., 2007). Additionally, Hypothesis 7 is supported by evidence that self-efficacy mediates the relationship between resource management and deep learning. Effective resource management provides students with comprehensive learning tools and supportive environments, essential for fostering deep engagement and knowledge integration. Self-efficacy acts as a crucial catalyst in translating these resources into meaningful learning outcomes (Lee & Choi, 2013; Hartnett, 2016).

Our findings also underscore the role of motivation as a mediator in the relationship between resource management and deep learning outcomes, supporting Hypothesis 9. Effective resource management strategies not only ensure resource availability but also create a motivating learning environment. Motivation drives persistence and cognitive engagement, and our study reveals that it influences deep learning outcomes both directly and indirectly through self-efficacy (Hsiao, 2021; Fırat et al., 2018).

Conclusion

Theoretical Contributions

This study contributes to the theoretical understanding of deep learning outcomes in virtual learning environments by elucidating the intricate relationships among resource management, motivation, self-efficacy, and student engagement. The findings highlight the significance of effective resource allocation and utilization in fostering deep learning engagement. By establishing resource management as a foundational predictor, this research enriches theoretical frameworks that explore the educational pathways leading to enhanced cognitive and critical thinking skills. Moreover, the identification of motivation and self-efficacy as mediators expands existing theoretical perspectives on the motivational factors influencing academic success in digital learning contexts.

Practical Implications

Practically, this study offers valuable insights for educators and educational policymakers aiming to optimize VLEs. By emphasizing the role of resource management, educators can enhance student access to diverse learning tools and supportive environments, thereby promoting deep learning experiences. Implementing structured support systems and fostering a motivating atmosphere can cultivate students' intrinsic motivation and self-efficacy, crucial for sustained engagement and academic achievement. These insights can guide the design of curriculum interventions and instructional strategies that prioritize resource accessibility and student empowerment in digital learning environments.

Recommendations

This paper recommends that educators focus on improving resource management by providing diverse and accessible learning tools and support systems. Additionally, motivational strategies should be implemented to engage students and foster their intrinsic interest in learning. Also, by integrating these findings into virtual learning frameworks, educational institutions can create environments that better support deep learning and improve student performance. Future research should consider exploring additional factors that influence deep learning and evaluating the effectiveness of specific resource management practices in various educational contexts.

References

Aguilar, S. J., Karabenick, S. A., Teasley, S. D., & Baek, C. (2021). Associations between learning analyticsdashboard exposure and motivation and self-regulated learning. Computers and Education/Computers & Education, 162, 104085. https://doi.org/10.1016/j.compedu.2020.104085

Aguirre-Urreta, M. I., & Hu, J. (2019). Detecting Common Method Bias. Data Base, 50(2), 45-70. https://doi.org/10.1145/3330472.3330477

Aharony, N. (2006). The use of deep and surface learning strategies among students learning English as a foreign language in an Internet environment. British Journal of Educational Psychology, 76(4), 851-866. https://doi.org/10.1348/000709905x79158

Alqurashi, E. (2016). Self-Efficacy In Online Learning Environments: A Literature Review. Contemporary Issues in Education Research, 9(1), 45-52. https://doi.org/10.19030/cier.v9i1.9549

Alyami, A., Abdulwahed, A., Azhar, A., Binsaddik, A., &Bafaraj, S. M. (2021). Impact of Time-Management on the Student‘s Academic Performance: A Cross-Sectional Study. Creative Education, 12(03), 471-485. https://doi.org/10.4236/ce.2021.123033

An, F., Xi, L., & Yu, J. (2023). The relationship between technology acceptance and self-regulated learning: the mediation roles of intrinsic motivation and learning engagement. Education and Information Technologies, 29(3), 2605-2623. https://doi.org/10.1007/s10639-023-11959-3

Bandura, A. (2011). On the Functional Properties of Perceived Self-Efficacy Revisited. Journal of Management, 38(1), 9-44. https://doi.org/10.1177/0149206311410606

Baumgartner, H., & Homburg, C. (2023). Factor Analysis. In Springer eBooks (pp. 1-35). https://doi.org/10.1007/978-3-319-05542-8_13-1

Bear, G. G., Slaughter, J. C., Mantz, L. S., & Farley-Ripple, E. (2017). Rewards, praise, and punitive consequences: Relations with intrinsic and extrinsic motivation. Teaching and Teacher Education, 65, 10-20. https://doi.org/10.1016/j.tate.2017.03.001

Bharathi, S. V., & Pande, M. B. (2024). Does constructivism learning approach lead to developing creative thinking skills? The mediating role of online collaborative learning environments. Journal of Computers in Education. https://doi.org/10.1007/s40692-024-00321-2

Biggs, J. B. (1988). Assessing student approaches to learning. Australian Psychologist, 23(2), 197-206. https://doi.org/10.1080/00050068808255604

Bradley, V. M. (2020). Learning Management System (LMS) Use with Online Instruction. International Journal of Technology in Education, 4(1), 68. https://doi.org/10.46328/ijte.36

Chang, C. Y., Panjaburee, P., Lin, H. C., Lai, C. L., & Hwang, G. H. (2022). Effects of online strategies on students‘ learning performance, self-efficacy, self-regulation and critical thinking in university online courses. Educational Technology Research and Development, 70(1), 185-204. https://doi.org/10.1007/s11423-021-10071-y

Chasetareh, F., Barabadi, E., Khajavy, G. H., & Flett, G. L. (2022). Perfectionism and L2 Achievement: The Mediating Roles of Motivation and Self-Regulated Learning Among Iranian High School Students. Journal of Psychoeducational Assessment, 41(1), 3-21. https://doi.org/10.1177/07342829221096916

Claessens, B. J., Van Eerde, W., Rutte, C. G., & Roe, R. A. (2007). A review of the time management literature. Personnel Review, 36(2), 255-276. https://doi.org/10.1108/00483480710726136

Coll, C., Rochera, M. J., & De Gispert, I. (2014). Supporting online collaborative learning in small groups: Teacher feedback on learning content, academic task and social participation. Computers and Education/Computers & Education, 75, 53-64. https://doi.org/10.1016/j.compedu.2014.01.015

Cronin-Golomb, L. M., & Bauer, P. J. (2023). Self-motivated and directed learning across the lifespan. Acta Psychologica, 232, 103816. https://doi.org/10.1016/j.actpsy.2022.103816

Duff, A. (2004). Understanding academic performance and progression of first-year accounting and business economics undergraduates: the role of approaches to learning and prior academic achievement. Accounting Education, 13(4), 409-430. https://doi.org/10.1080/0963928042000306800

Eden, N. C. A., Chisom, N. O. N., & Adeniyi, N. I. S. (2024). Harnessing technology integration in education: Strategies for enhancing learning outcomes and equity. World Journal of Advanced Engineering Technology and Sciences, 11(2), 001-008. https://doi.org/10.30574/wjaets.2024.11.2.0071

Emiru, E. K., & Gedifew, M. T. (2024). The effect of teacher self-efficacy on learning engagement of secondary school students. Cogent Education, 11(1). https://doi.org/10.1080/2331186x.2024.2308432

Esteban-Guitart, M., & Gee, J. (2020). ―Inside the Head and Out in the World‖. An Approach to Deep Teaching and Learning. Multidisciplinary Journal of Educational Research, 10(1), 1. https://doi.org/10.17583/remie.2020.4868

Everaert, P., Opdecam, E., &Maussen, S. (2017). The relationship between motivation, learning approaches, academic performance and time spent. Accounting Education, 26(1), 78-107. https://doi.org/10.1080/09639284.2016.1274911

Fırat, M., Kılınç, H., &Yüzer, T. V. (2017). Level of intrinsic motivation of distance education students in e-learning environments. Journal of Computer Assisted Learning, 34(1), 63-70. https://doi.org/10.1111/jcal.12214

Hair, J. F., Sarstedt, M., Hopkins, L., &Kuppelwieser, V. G. (2014). Partial least squares structural equation modeling (PLS-SEM). European Business Review, 26(2), 106-121. https://doi.org/10.1108/ebr-10-2013-0128

Harackiewicz, J. M., Smith, J. L., &Priniski, S. J. (2016). Interest Matters. Policy Insights from the Behavioral and Brain Sciences, 3(2), 220-227. https://doi.org/10.1177/2372732216655542

Hartnett, M. (2016). The Importance of Motivation in Online Learning. In Springer eBooks (pp. 5-32). https://doi.org/10.1007/978-981-10-0700-2_2

Hatlevik, O. E., & Bjarnø, V. (2021). Examining the relationship between resilience to digital distractions, ICT self-efficacy, motivation, approaches to studying, and time spent on individual studies. Teaching and Teacher Education, 102, 103326. https://doi.org/10.1016/j.tate.2021.103326

Hatlevik, O. E., Throndsen, I., Loi, M., & Gudmundsdottir, G. B. (2018). Students' ICT self-efficacy and computer and information literacy: Determinants and relationships. Computers and Education/Computers & Education, 118, 107-119. https://doi.org/10.1016/j.compedu.2017.11.011

Hatlevik, O. E., Throndsen, I., Loi, M., & Gudmundsdottir, G. B. (2018b). Students' ICT self-efficacy and computer and information literacy: Determinants and relationships. Computers and Education/Computers & Education, 118, 107-119. https://doi.org/10.1016/j.compedu.2017.11.011

Henseler, J., Ringle, C. M., & Sarstedt, M. (2014). A new criterion for assessing discriminant validity in variance-based structural equation modeling. Journal of the Academy of Marketing Science, 43(1), 115-135. https://doi.org/10.1007/s11747-014-0403-8

Hsiao, S. C. (2021). Effects of the Application of Virtual Reality to Experiential Education on Self-Efficacy and Learning Motivation of Social Workers. Frontiers in Psychology, 12. https://doi.org/10.3389/fpsyg.2021.770481

Ilishkina, D. I., De Bruin, A., Podolskiy, A. I., Volk, M. I., & Van Merriënboer, J. J. (2022). Understanding self-regulated learning through the lens of motivation: Motivational regulation strategies vary with students' motives. International Journal of Educational Research, 113, 101956. https://doi.org/10.1016/j.ijer.2022.101956

Ito, T., & Umemoto, T. (2023). Examining the causal model between socially shared regulation of motivation, engagement, and creative performance. Thinking Skills and Creativity, 48, 101288. https://doi.org/10.1016/j.tsc.2023.101288

Jiang, R. (2022). Understanding, Investigating, and promoting deep learning in language education: A survey on chinese college students' deep learning in the online EFL teaching context. Frontiers in Psychology, 13. https://doi.org/10.3389/fpsyg.2022.955565

Khamparia, A., & Pandey, B. (2017). Impact of Interactive Multimedia in E-Learning Technologies. In Advances in higher education and professional development book series (pp. 171-199). https://doi.org/10.4018/978-1-5225-2489-2.ch007

Kumar, S., Sahoo, S., Lim, W. M., Kraus, S., &Bamel, U. (2022). Fuzzy-set qualitative comparative analysis (fsQCA) in business and management research: A contemporary overview. Technological Forecasting & Social Change/Technological Forecasting and Social Change, 178, 121599. https://doi.org/10.1016/j.techfore.2022.121599

Lee, D., Watson, S. L., & Watson, W. R. (2020). The Relationships Between Self-Efficacy, Task Value, and Self-Regulated Learning Strategies in Massive Open Online Courses. International Review of Research in Open and Distance Learning, 21(1), 23-39. https://doi.org/10.19173/irrodl.v20i5.4389

Legault, L. (2016). Intrinsic and Extrinsic Motivation. In Springer eBooks (pp. 1-4). https://doi.org/10.1007/978-3-319-28099-8_1139-1

Li, S., & Zheng, J. (2018). The Relationship Between Self-efficacy and Self-regulated Learning in One-to-One Computing Environment: The Mediated Role of Task Values. ˜the œAsia-Pacific Education Researcher, 27(6), 455-463. https://doi.org/10.1007/s40299-018-0405-2

Lindblom-Ylänne, S., & Lonka, K. (1998). Individual ways of interacting with the learning environment — are they related to study success? Learning and Instruction, 9(1), 1-18. https://doi.org/10.1016/s0959-4752(98)00025-5

List, A., &Nadasen, D. (2016). Motivation and Self-regulation in Community College Transfer Students at a Four-year Online University. Community College Journal of Research and Practice, 41(12), 842-866. https://doi.org/10.1080/10668926.2016.1242096

Liu, H., Yao, M., Li, R., & Zhang, L. (2019). The relationship between regulatory focus and learning engagement among Chinese adolescents. Educational Psychology, 40(4), 430-447. https://doi.org/10.1080/01443410.2019.1618441

Lu, N. Q., & Rameli, N. M. R. M. (2023). How Academic Self-Efficacy Influences Online Learning Engagement: The Mediating Role of Boredom. International Journal of Interactive Mobile Technologies, 17(24), 115-135. https://doi.org/10.3991/ijim.v17i24.44759

Macalisang, D. S., &Bonghawan, R. G. G. (2024). Teachers' Learning Reinforcement: Effects on Students' Motivation, Self Efficacy and Academic Performance. International Journal of Scientific Research and Management, 12(02), 3218-3228. https://doi.org/10.18535/ijsrm/v12i02.el08

Marshall, S., & Sankey, M. D. (2023). The Future of the Learning Management System in the Virtual University. In University development and administration (pp. 283-304). https://doi.org/10.1007/978-981-99-4170-4_16

McGill, C. M., Ali, M., & Barton, D. (2020). Skills and Competencies for Effective Academic Advising and Personal Tutoring. Frontiers in Education, 5. https://doi.org/10.3389/feduc.2020.00135

Nieminen, J. H., Asikainen, H., & Rämö, J. (2019). Promoting deep approach to learning and self-efficacy by changing the purpose of self-assessment: a comparison of summative and formative models. Studies in Higher Education, 46(7), 1296-1311. https://doi.org/10.1080/03075079.2019.1688282

Núñez, J. L., & León, J. (2016). The Mediating Effect of Intrinsic Motivation to Learn on the Relationship between Student´s Autonomy Support and Vitality and Deep Learning. ˜the œSpanish Journal of Psychology, 19. https://doi.org/10.1017/sjp.2016.43

Orr, D., Rimini, M., & Van Damme, D. (2015). Open Educational Resources. In Educational research and innovation. https://doi.org/10.1787/9789264247543-en

Oudeyer, P. Y., & Kaplan, F. (2007). What is intrinsic motivation? A typology of computational approaches. Frontiers in Neurorobotics, 1. https://doi.org/10.3389/neuro.12.006.2007

Pan, X. (2023). Online Learning Environments, Learners' Empowerment, and Learning Behavioral Engagement: The Mediating Role of Learning Motivation. SAGE Open, 13(4). https://doi.org/10.1177/21582440231205098

Pannekoek, F., & Ally, M. (2008). The Theory and Practice of Online Learning. In Athabasca University Press eBooks. https://doi.org/10.15215/aupress/9781897425084.01

Prameswioro, I. S., Fathurrochman, I., Sembing, D., Bangkara, B. A., &Sudrajat, D. (2023). Relevance between Blended Learning and Students' Independent Learning Curriculum: An Overview of Digital Age Education, Student and Teacher Engagement, Technological Resources. JurnalKependidikan, 9(3), 858. https://doi.org/10.33394/jk.v9i3.8320

Prifti, R. (2020). Self-efficacy and student satisfaction in the context of blended learning courses. Open Learning, 37(2), 111-125. https://doi.org/10.1080/02680513.2020.1755642

Pumptow, M., & Brahm, T. (2020). Students' Digital Media Self-Efficacy and Its Importance for Higher Education Institutions: Development and Validation of a Survey Instrument. Technology, Knowledge and Learning, 26(3), 555-575. https://doi.org/10.1007/s10758-020-09463-5

Quynh, N. H., Hoai, N. T., & Thu, N. (2021). The roles of student engagement motivations in learning and managing. Deleted Journal, 9(4), 223-234. https://doi.org/10.31686/ijier.vol9.iss4.3043

Ramsden, P. (1979). Student learning and perceptions of the academic environment. Higher Education, 8(4), 411-427. https://doi.org/10.1007/bf01680529

Rani, R., Radhakrishnan, R., Sable, A., Srinivas, V., & Prasad, K. (2023). Development of self-education motivation for students using time management techniques in primary and high school teachers. GeSec, 14(9), e2526. https://doi.org/10.7769/gesec.v14i9.2526
Rashid, T., & Asghar, H. M. (2016). Technology use, self-directed learning, student engagement and academic performance: Examining the interrelations. Computers in Human Behavior, 63, 604-612. https://doi.org/10.1016/j.chb.2016.05.084
Richardson, J. C., & Newby, T. (2006). The Role of Students' Cognitive Engagement in Online Learning. ˜the œAmerican Journal of Distance Education, 20(1), 23-37. https://doi.org/10.1207/s15389286ajde2001_3
Richardson, M., Abraham, C., & Bond, R. (2012). Psychological correlates of university students' academic performance: A systematic review and meta-analysis. Psychological Bulletin, 138(2), 353-387. https://doi.org/10.1037/a0026838
Rojo, A. (2015). Translation meets cognitive science: The imprint of translation on cognitive processing. Multilingua, 34(6). https://doi.org/10.1515/multi-2014-0066
Rotar, O. (2022). Online student support: a framework for embedding support interventions into the online learning cycle. Research and Practice in Technology Enhanced Learning/Research and Practice in Technology Enchanced Learning, 17(1). https://doi.org/10.1186/s41039-021-00178-4
Sarstedt, M., Ringle, C. M., & Hair, J. F. (2021). Partial Least Squares Structural Equation Modeling. In Springer eBooks (pp. 1-47). https://doi.org/10.1007/978-3-319-05542-8_15-2
Segooa, M. A., & Kalema, B. M. (2015). Virtual Learning Environments for Higher Learning Institutions in Developing Countries. https://doi.org/10.1109/econf.2015.67
Sherer, M., Maddux, J. E., Mercandante, B., Prentice-Dunn, S., Jacobs, B., & Rogers, R. W. (1982). The Self-Efficacy Scale: Construction and Validation. Psychological Reports, 51(2), 663-671. https://doi.org/10.2466/pr0.1982.51.2.663
Shroff, R. H., Vogel, D. R., Coombes, J., & Lee, F. (2007). Student E-Learning Intrinsic Motivation: A Qualitative Analysis. Communications of the Association for Information Systems, 19. https://doi.org/10.17705/1cais.01912
Sølvik, R. M., & Glenna, A. E. H. (2021). Teachers' potential to promote students' deeper learning in whole-class teaching: An observation study in Norwegian classrooms. Journal of Educational Change, 23(3), 343-369. https://doi.org/10.1007/s10833-021-09420-8
Stanikzai, M. I. (2023). Critical Thinking, Collaboration, Creativity and Communication Skills among School Students: A Review Paper. European Journal of Theoretical and Applied Sciences, 1(5), 441-453. https://doi.org/10.59324/ejtas.2023.1(5).34
Suan, A. F. (2023). Self-Regulation as an Antecedent of Academic Achievement: A Mixed Method Study. British Journal of Multidisciplinary and Advanced Studies, 4(4), 20-43. https://doi.org/10.37745/bjmas.2022.0246
Tang, H., Dai, M., Du, X., Hung, J. L., & Li, H. (2023). Understanding college students' cognitive engagement in online collaborative problem-solving: A multimodal data analysis. Distance Education, 44(2), 306-323. https://doi.org/10.1080/01587919.2023.2209025
Tualaulelei, E., Burke, K., Fanshawe, M., & Cameron, C. (2021). Mapping pedagogical touchpoints: Exploring online student engagement and course design. Active Learning in Higher Education, 23(3), 189-203. https://doi.org/10.1177/1469787421990847
Van Geel, M., Keuning, T., Meutstege, K., De Vries, J., Visscher, A., Wolterinck, C., Schildkamp, K., &Poortman, C. (2023). Adapting Teaching to Students' Needs: What Does It Require

from Teachers? In Springer eBooks (pp. 723-736). https://doi.org/10.1007/978- 3-031-31678-4_33

Vansteenkiste, M., Ryan, R. M., &Soenens, B. (2020). Basic psychological need theory: Advancements, critical themes, and future directions. Motivation and Emotion, 44(1), 1–31. https://doi.org/10.1007/s11031-019-09818-1

Vörösmarty, G., & Dobos, I. (2020). Green purchasing frameworks considering firm size: a multicollinearity analysis using variance inflation factor. Supply Chain Forum, 21(4), 290–301. https://doi.org/10.1080/16258312.2020.1776090

Wang, S., & Zhang, D. (2018). Student-centred teaching, deep learning and self-reported ability improvement in higher education: Evidence from Mainland China. Innovations in Education and Teaching International, 56(5), 581-593. https://doi.org/10.1080/14703297.2018.1490662

Weng, C., Chen, C., & Ai, X. (2022). A pedagogical study on promoting students' deep learning through design-based learning. International Journal of Technology and Design Education, 33(4), 1653-1674. https://doi.org/10.1007/s10798-022-09789-4

Wilding, J., & Andrews, B. (2006). Life goals, approaches to study and performance in an undergraduate cohort. British Journal of Educational Psychology, 76(1), 171-182. https://doi.org/10.1348/000709904x24726

Wu, X. Y. (2023). Exploring the effects of digital technology on deep learning: a meta-analysis. Education and Information Technologies, 29(1), 425-458. https://doi.org/10.1007/s10639-023-12307-1

Zhan, Y., Jiang, Y., Wan, Z. H., & Guo, J. J. (2020). Is There an ―Expectancy × Value‖ Effect? Investigating the Impact of Self-Efficacy and Learning Motives on Chinese Undergraduates' Use of Deep Language Learning Strategies. ˜the œAsia-Pacific Education Researcher, 30(1), 83-94. https://doi.org/10.1007/s40299-020-00516-y

Zhao, J., & Qin, Y. (2021). Perceived Teacher Autonomy Support and Students' Deep Learning: The Mediating Role of Self-Efficacy and the Moderating Role of Perceived Peer Support. Frontiers in Psychology, 12. https://doi.org/10.3389/fpsyg.2021.652796

Zhu, M., Bonk, C. J., & Doo, M. Y. (2020). Self-directed learning in MOOCs: exploring the relationships among motivation, self-monitoring, and self-management. Educational Technology Research and Development, 68(5), 2073-2093. https://doi.org/10.1007/s11423-020-09747-8

Zitha, I., Mokganya, G., &Sinthumule, O. (2023). Innovative Strategies for Fostering Student Engagement and Collaborative Learning among Extended Curriculum ProgrammeStudents. Education Sciences, 13(12), 1196. https://doi.org/10.3390/educsci13121196

Zou, H., Yao, J., Zhang, Y., & Huang, X. (2023). The influence of teachers' intrinsic motivation on students' intrinsic motivation: The mediating role of teachers' motivating style and teacher-student relationships. Psychology in the Schools, 61(1), 272-286. https://doi.org/10.1002/pits.23050