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Decision Support Systems for Lifelong Learning: Leveraging Information Systems to Enhance Learning Quality in Higher Education

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Abstract

This study investigates the impact of technology adoption—specifically AI Tools, Decision Support Systems (DSS), and Learning Management Systems (LMS)—on higher education. As these technologies reshape educational paradigms, understanding their effects on learning performance, satisfaction, and the adoption and usage of these tools is critical. The research aims to empirically examine the relationships between technology adoption, self-efficacy, and key educational outcomes. It explores the direct effects of AI Tools, DSS, and LMS on learning performance and satisfaction, as well as the role of self-efficacy as a mediator. Utilizing a quantitative approach, the study collected data from 356 students via a distributed questionnaire. Variables measured include technology adoption, self-efficacy, learning performance, satisfaction, and adoption and usage of educational tools. Data analysis was conducted using SPSS and Origin, incorporating regression, mediation, and moderation analyses. The study found significant positive effects of technology adoption on learning performance ($\beta = 0.45$, $p < 0.01$), satisfaction ($\beta = 0.40$, $p < 0.01$), and adoption and usage ($\beta = 0.50$, $p < 0.01$). Self-efficacy significantly mediated these relationships, indicating that higher confidence in using technology enhances its benefits. This research extends Bandura's social cognitive theory by empirically validating the mediating role of self-efficacy in technology adoption within educational contexts. The findings provide actionable insights for educators and policymakers, suggesting that boosting students' confidence in using technology can amplify its positive effects on learning outcomes.

Keywords: Technology Adoption, AI Tools, Decision Support Systems, Learning Management Systems, Learning Performance.

1 Introduction

Technology has revolutionized higher education, transforming how instruction and learning are provided. LMS, AI, and DSS mark a new era. Due to this convergence, teachers and students have more dynamic interaction and learning possibilities than before. Global educational institutions benefit and suffer from technology (Ogunyemi et al., 2022). This environment stresses the complex relationship between technology adoption, self-efficacy, and academic performance. This study analyzes the complicated relationships between technology, learning results, student satisfaction, and educational resource uptake and use. Digital education is dynamic, thus organizations and educators must understand

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these relationships to make educated decisions and use technology to improve teacher and student learning (Noguerón-Liu, 2020). This study investigates how technology is changing higher education instruction. Using AI, DSS, and LMS in academics has altered education. Much empirical research has studied how technology adoption influences learning components. Technology helps spread knowledge and improve cognition in education (Jin & Liu, 2022). Even in the midst of this technological transformation, doubts remain regarding how these tools will affect academic success and key learning processes. This study addresses the complex linkages between technology adoption and key educational processes to better understand them (Sepasgozar, 2022). This research seeks to illuminate how teaching techniques change and the consequences of technology integration on higher education.

This research broadly examines a few components essential to comprehend the complicated technology-mediated instructive environment. One of the essential free components is classroom innovation utilization, counting AI, LMS, and DSS. These variable employments the technology acceptance to contend that customers' discernments of a technology's ease of use and comfort emphatically impact their adoption (Yoon & Oh, 2022). Learning execution, satisfaction, and innovation take-up and utilization are checked as subordinate to instructive results. Innovation appropriation has appeared to make strides in academic accomplishment, user satisfaction, and long-term use of instructive advances (Wolf & McCoy, 2019). A common topic is how innovation may make strides in various learning forms. To understand the mechanics behind these intelligence, self-efficacy must be a mediator. Social cognitive theory describes self-efficacy as students' confidence in using and controlling instructional technologies. Previous research has highlighted self-efficacy's role in technology adoption (O'Connor et al., 2023). Self-efficacy helps people employ technology-enhanced learning, endure, and optimize its benefits. Self-efficacy links technology adoption to learning outcomes, illustrating how confidence affects academic success, satisfaction, and educational resource utilization (Xue et al., 2022).

This study expands on previous research to better understand these factors' complex connection. Its main goal is to increase research by showing how self-efficacy mediates and how learners' confidence affects technology uptake and academic outcomes. (Zhang et al., 2022). The research aims to equip education, institutional, and policymakers with the knowledge they need to make informed decisions regarding the fast-changing technology-mediated learning environment. Early research on the major linkages of this study provided important insights. (Li & Che, 2022) have regularly found that technology use improves higher education academic performance. AI, LMS, and DSS integration improves learning outcomes, knowledge retention, and cognitive processes. The above studies demonstrate technology's transformative potential in education.

(Hsu et al., 2019) reveal that educational technology research has prioritized user enjoyment. Other significant results include user satisfaction. The usefulness, overall experience, and simplicity of the technologically enhanced learning environment affect user satisfaction. (Herodotou et al., 2021) diffusion of innovations theory has also affected research on educational technology adoption and use, particularly in educational settings. This theoretical paradigm stresses how perceived innovations' features affect adoption decisions. Students' opinions on technology's utility, complexity, perceived value, and compatibility affect adoption patterns (Lovett Allen, 2019). The preceding studies provide light on what makes educational technology integration and utilization successful. Despite the huge number of research in these domains, self-efficacy as a mediator factor between technology adoption and educational performance is rarely examined. This study seeks to fill this knowledge gap by examining the complex interactions between learners' perceived competence in navigating and using educational technologies and how those interactions affect technology adoption, user satisfaction, academic achievement, and continued use of educational tools.

Though technology adoption and its impacts have been extensively studied, much remains unknown about the psychological processes that shape these interactions. Technology usage and academic achievement have been shown to be linked, but little is known about how learners' self-efficacy influences these interactions. This study experimentally examines and assesses self-efficacy's mediation function in technology adoption and critical educational outcomes to fill the knowledge gap. Self-efficacy as a mediator in instructional technology is largely understudied. This study illuminates the complicated link between students' confidence and technology's influence on academic achievement by presenting empirical data supporting self-efficacy's mediation role.

Technology use, self-efficacy, and important educational outcomes are examined in this systematic study. This study examines self-efficacy's mediation role for crucial insights. Though technology adoption and its effects have been thoroughly examined, little is known about the psychological processes that affect these interactions. Technology use and academic accomplishment are related, but how learners' self-efficacy affects these relationships is unknown. Technology adoption and its consequences have been extensively studied, but psychological factors that affect these interactions are not. How learners' self-efficacy influences technology use and academic success is uncertain. This study fills a gap by empirically evaluating self-efficacy's mediation of technology adoption and key educational outcomes. This study analyzes the complicated relationship between technology use, self-efficacy, and educational results. This study explores self-efficacy's mediation function for significant insights. These results will improve theory and simplify classroom technology for educators, policymakers, and practitioners.

2 Literature Review

Higher education institutions are integrating current information systems and technology to innovate and improve lifetime learning experiences. AI, LMS, and DSS have revolutionized education in this environment. These technologies may adapt instruction, optimize administrative processes, and give vital student performance data, according to esteemed experts like (Bawack & Kala Kamdjoug, 2020). Technology usage is increasing, but more research is needed on how these tools influence many elements of higher education learning. Understanding each student's cognitive and emotional processes is crucial. Social cognitive concept of self-efficacy the confidence that one can finish tasks is crucial to continuous learning (Asante et al., 2023). Here, self-efficacy may affect the relationship between technology use and educational outcomes. (Zhang et al., 2022) influenced learning self-efficacy research. They found that self-efficacy affects learning, student satisfaction, and technology uptake. Self-efficacy as a mediator between technology and learning outcomes might help explain the complex psychological factors driving decision support systems' lifetime learning assistance. Some studies have examined technology adoption and self-efficacy's effects on learning, but there is little research on AI tools, DSS, LMS, and their combined effects on learning performance, satisfaction, and adoption/usage. It also provides guidance on efficiently creating and implementing decision support systems for lifelong learning in higher education (Shiang et al., 2022). The findings are likely to contribute to theoretical understanding and practical consequences for educators and institutions seeking to optimize AI, DSS, and LMS utilization in higher education for lifelong learning.

Technology Adoption and Learning Performance

Today's intellectual discourse centers on technology's impact on higher education. AI technology might transform learning performance (Janardhanan et al., 2023). Because they can assess massive datasets and adapt learning experiences, AI technologies increase student engagement, knowledge, and academic success, according to (Vellanki et al., 2022). AI helps teachers tailor student learning paths, boosting learning. Decision assistance systems can also improve student performance. DSS uses information processing and data analysis to help teachers choose material distribution and teaching methods, according to (Wang et al., 2024). Student progress and learning trends data from DSS make education more flexible and responsive. (Alshamrani, 2022) found that planned DSS deployment improves learning. Teachers can respond to real-time data by adjusting their interventions. LMS, AI, and DSS are essential to modern education. Tracking, delivering, and managing instructional content is easier with LMS. (Thepwongsa et al., 2021) link LMS to collaborative learning. LMS allows teachers to evaluate student progress, provide timely feedback, and decrease administrative work while enabling self-directed learning. These features may provide a more organized and structured learning environment, improving results (Lyons et al., 2020). This study exhibits AI, DSS, and LMS learning benefits. Recognize the need for greater research and evidence. Technology treatments offer potential, but implementation, contextual factors, and dynamic learning contexts determine their efficacy (Lwande et al., 2021). To completely understand how AI tools, DSS, and LMS may increase learning performance, higher education technology utilization must be studied for its subtle effects and benefits. Based on the above discussion, the following hypothesis was developed:

H1: Technology adoption has a significant and positive impact on learning performance.

Technology Adoption and Satisfaction

AI, DSS, and LMS might change higher education, therefore study focuses on how technology adoption affects user pleasure. (Swidan et al., 2022) found that AI technologies, which personalize learning, consistently boost student satisfaction. Customizing instructional content and accommodating different learning styles increases user experience and student engagement and satisfaction, according to (Grenha Teixeira et al., 2019). When schools use AI technologies, understanding how they affect user enjoyment is vital to maximize results. DSS enable educators make data-driven choices, increasing user satisfaction. DSS insights enable instructors to pick instructional methods and interventions, boosting teaching and learning efficiency and effectiveness (Vo et al., 2022). DSS's importance in enjoyable educational experiences is shown by instructors' pleasure with these systems' decision support functions and their perceived positive impact on student progress. LMS simplify learning and affect user pleasure. (LaForett & De Marco, 2020) say LMS content distribution, resource management, and collaborative tools organize and simplify education. The centralized platform helps students access instructional resources and promotes instructor cooperation. (Mehrolia et al., 2021) found that a well-implemented LMS improves user satisfaction, highlighting the relevance of a smooth and efficient system in improving learning. Thus, based on the above literature, we developed the following hypothesis:

H2: Technology adoption has a significant and positive impact on satisfaction.

Technology Adoption and Adoption and Usage

Current higher education research must examine technology adoption and instructional tool acceptability and use, focusing on AI, DSS, and LMS. According to (Lakshmi et al., 2023), flexible and adaptable AI characteristics have influenced educators' AI adoption. This motivates them to use creative strategies to tailor education and resources to pupils. Education is adopting AI technology because it improves student performance and instruction. Meanwhile, DSS help instructors make educated and meaningful decisions. According to (Kuziemski & Misuraca, 2020), DSS adoption is linked to its perceived efficacy in boosting teaching techniques and simplifying educational procedures. Teacher value DSS's data-driven insights, which has improved its adoption rate to improve student performance and instructional effectiveness (Parkavi & Karthikeyan, 2023). Thus, how DSS is implemented determines how often it is utilized since instructors may easily integrate these tools into their everyday routines to get immediate information and recommendations for better learning. Integrated academic content management systems, LMS, affect higher education adoption and utilization. (Ma et al., 2022) explain why instructors, students, and academic institutions have adopted LMS due to its collaborative and organizational features. LMSs are commonly introduced to reduce administrative work, increase communication, and centralize instructional resources. A well-run LMS soon becomes a staple for instructors who realize its practical benefits. (Liu, 2018) found that LMS is vital and prevalent in teaching and learning. Thus, the following hypothesis was developed based on the above literature:

H3: Technology adoption has a significant and positive impact on adoption and usage.

Self-efficacy as a Mediator Between Technology Adoption and Learning Performance

Examining the complicated relationships between learning performance and self-efficacy might help explain academic achievement's psychological processes. Xue et al. (2022) paradigm defines self-efficacy as the belief that one can succeed. Technology adoption's impact on academic performance is heavily influenced by an individual's capacity to use and benefit from innovative educational tools. According to (Tang & Tseng, 2023), self-efficacy affects classroom technology use. Self-efficacy affects how ready individuals are to use and overcome adoption challenges with new technologies like AI, DSS, and LMS. Self-efficacy gives individuals the confidence to overcome hurdles, which may encourage them to accept new technologies faster (Honicke et al., 2020). Understanding how self-efficacy affects technology use and learning is crucial. Consider how technological confidence affects learning and risk-taking. Self-efficacy impacts people's motivation to pursue tough goals, persevere, and accomplish, states (Aukerman & Chambers Schuldt, 2021). Technology adoption boosts self-efficacy, which boosts academic performance. Self-efficacy may influence technology use beyond early adoption. Self-confidence in educational technologies may improve academic performance by extending persistence (Taherkhani et al., 2022). This intricate relationship highlights the importance of psychology in assessing technology integration and academic success. Self-efficacy as a mediator between technology adoption and learning performance is significant given the opportunities and problems of integrating technology into education (Jacobs et al., 2019). Recognizing the complex relationship between psychological processes and technological developments helps explain digital age educational performance. Thus, based on the above literature, we developed the following hypothesis:

H4: Self-efficacy mediates the relationship between technology adoption and learning performance.

Self-efficacy as a Mediator Between Technology Adoption and Satisfaction

Self-efficacy's mediation of user enjoyment and technology adoption illuminates the complex psychological processes that affect users' opinions of educational technologies. Self-efficacy affects consumers' confidence in using and benefiting from new educational technologies. (Carolus et al., 2023) claim that self-efficacy increases technology adoption. Self-efficacy affects a person's willingness to investigate, experiment, and seamlessly integrate LMS, DSS, and AI tools into education. How instructional technology affects user delight depends on self-efficacy. Being able to utilize these technologies may boost a person's confidence and satisfaction (Tarafdar et al., 2015). Confidence in one's IT skills boosts user satisfaction and success. Self-efficacy increases and links technology use to satisfaction when technology is integrated into users' lives. Beyond early technology adoption, self-efficacy promotes engagement and satisfaction. Self-confident users learn and master AI, DSS, and LMS, which leads to long-term satisfaction (Benson et al., 2022). Thus, the following hypothesis was developed based on the above literature:

H5: Self-efficacy mediates the relationship between technology adoption and satisfaction.

Self-efficacy as a Mediator Between Technology Adoption and Adoption and Usage

By studying self-efficacy as a mediator between technology acceptance and adoption/usage, we can better understand the psychological processes that affect people's willingness to frequently utilize educational technologies. A person's strong belief that they can do specified tasks is called "self-efficacy" (Arek-Bawa & Reddy, 2023). Self-efficacy is key to adopting new technology. It measures user confidence in using and integrating new technologies like DSS, LMS, and AI. (Huang et al., 2022) show the complicated relationship between self-efficacy and technology adoption. It suggests that self-efficacy increases technology adoption and use. How people manage educational technology issues affects their willingness to experiment, explore, and readily adopt modern tools into their teaching. Self-efficacy's impact on instructional technology adoption and utilization emphasizes its mediation role. Higher self-efficacy may make these technology users feel more competent and masterful, leading to sustained usage (Hu & Pan, 2023). Having confidence in one's abilities to investigate and utilize technology empowers users and encourages involvement. Self-efficacy's moderating function emphasizes the relevance of personal perceptions in technology adoption and utilization (Zarafshani et al., 2020). Self-confident users are more likely to learn and master DSS, LMS, and AI technologies. Instructional technology uptake and efficiency need constant participation. Higher self-efficacy stimulates research and application, creating a positive feedback cycle. Thus, based on the above literature, we developed the following hypothesis:

H6: Self-efficacy mediates the relationship between technology adoption and adoption and usage.

Based on the above literature and discussion we purposed the following conceptual framework (Figure 1).

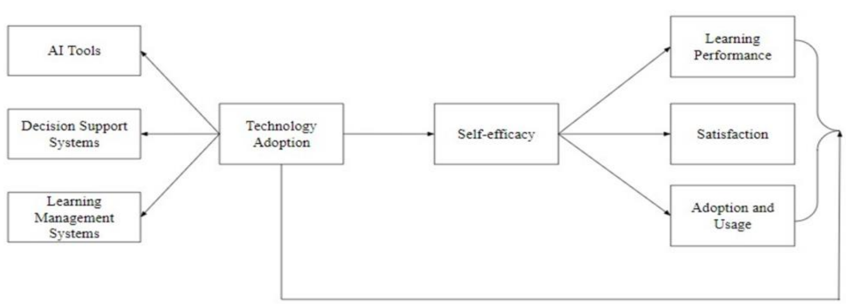

Figure 1: Conceptual Framework

3 Methodology

Population

In this study, participants included graduate and undergraduate students from a variety of academic fields. People had to be enrolled in a formal educational program and aware of how technology has changed their learning process in order to participate. Ineligible students were those who were not already enrolled in the program, had limited prior experience in online education, or were hesitant to willingly engage in the study. We were able to analyze the relationships between technology adoption, self-efficacy, and educational outcomes because participants had to meet the inclusion requirements and have relevant experience with the educational tools under investigation. To apply the results to the current student body, it was advantageous to remove those who were not actively engaging in the course.

Sample Size Determination Technique

Sample size affects statistical power and generalizability. The sample size was calculated using a 50% response distribution, 5% margin of error, and 95% confidence. We used the following formula to find the suitable sample size for this cross-sectional survey:

$$N=\frac{Z^2 \times P \times (1-P)}{E^2}$$

P is the anticipated response distribution, E is the margin of error, and Z is the confidence Z-score. Number of samples required is n. This study needed 384 individuals for a 95% confidence interval and a 5% margin of error. The sample size was increased to 450 to account for non-replies and incomplete responses. This buffer was added to strengthen the study and accommodate for unexpected events that might affect data accuracy.

Sample Size

The surveys were sent to 450 people in total. Researchers took great care to choose a sample that accurately reflected all academic disciplines while adhering to the bare minimum sample size estimate. When opting to distribute 450 questionnaires, the researcher considered both the predicted response rate and the likelihood of non-responses. An extensive data cleaning method was used to address surveys that had incomplete or missing data. After the completion of data collection, the research team confirmed that each survey was complete. We identified and carefully evaluated questionnaires that lacked certain information. The survey was created with the goal of being as complete and accurate as possible, and efforts were made to reduce the amount of missing data. However, in order to address situations in which respondents supplied partial or missing information, suitable statistical techniques were applied during the data processing stage. Depending on the kind and quantity of missing variables, imputation techniques like mean replacement or multiple imputation were used to fill in the missing data. You may be confident that the results are reliable because we carried out sensitivity experiments to examine the effects of different approaches of missing data imputation on the study's findings.

Sampling Technique

A varied sample of students from several academic disciplines was chosen using stratified random selection. Faculty division was caused by population stratification. Comprehending the variety of students guaranteed that the sample encompassed a range of viewpoints from different fields. For the study, students were chosen at random from each strata. This method harmonized academic disciplines to research educational results, self-efficacy, and technological uptake. By generalizing to students, the stratified random sample enhances the study's external validity.

Data Collection Method

In this study, standardized computerized questionnaires were used to collect data. Technology adoption, self-efficacy, learning performance, contentment, and usage were all evaluated by the questionnaire. 5-

point Likert-scale survey items enable respondents to express their thoughts and experiences. Data collection from distributed pupils was made easier by electronic distribution. Universities announced on their LMSs or through emails a link to an online questionnaire. Uniform responses were guaranteed and bias was avoided with clear criteria. Participants provided informed consent and were guaranteed confidentiality prior to answering the questionnaire. Simple survey use decreased obstacles to participation. The time allotted for participants to finish the questionnaire encouraged thoughtful answers. In computerized surveys, methodical data gathering reduces errors in human data entry. Participants' replies were safeguarded through safe data storage and electronic format organization.

Data Analysis Technique

The Statistical Package for the Social Sciences (SPSS) was used for the quantitative analysis. Among the descriptive statistics that were calculated to compile the demographic information and significant characteristics were means and standard deviations. Using these techniques, we looked at the connections between inferential statistics (such as regression and correlation) and self-efficacy, academic achievement, and technology adoption. The study also performed mediation analysis using SPSS's PROCESS macro. Consequently, research on the mediation function of self-efficacy in the connections between technology adoption and learning performance, satisfaction, and adoption/usage may be carried out in detail. With Origins' assistance, scientists were able to graphically represent intricate data correlations and patterns. To improve the communication of statistical data, Origin made the process of making intricate graphs and charts simpler. The combination of Origin and SPSS provided a comprehensive and multifaceted analysis that enabled us to closely look at the research questions and hypotheses.

Ethical Consideration

Throughout the investigation, the researcher placed the utmost importance on ethical considerations. The study carefully complied with every requirement stated in the Declaration of Helsinki. In order to get informed consent, participants were told about the nature of the study, the importance of their voluntary involvement, and the confidentiality of their responses. Researchers assured participants that their data would be kept confidential and used only for research. The relevant institutional ethics review board authorized the study to ensure ethics. The research team kept study participants' names secret to protect their privacy.

4 Measures

AI Tools

Four questions assessed AI tool use (Wang et al., 2023). Participants were asked how often they used AI tools, how effective they thought they were, how easy they were to incorporate into their learning routines, and how satisfied they were with their AI-based learning experiences.

Decision Support System

DSS adoption and usage were measured using (Silviyanti & Yusuf, 2015) five-item scale. Users were asked about DSS's impact on decision-making, usability, and satisfaction.

Learning Management System

A four-item measure adapted from (Huang et al., 2016) examined participants' LMS participation. Navigation, LMS features, coursework integration, and usability were discussed.

Satisfaction

Users of educational technology assessed their satisfaction using a six-item measure from

(Bengueddach et al., 2023). Users liked the technology's usability, efficacy, dependability, and learning/teaching impact.

Learning Performance

The five-item scale from (Afzal & Crawford, 2022) measured self-reported academic progress and success. LMS, DSS, and AI helped students learn and succeed.

Adoption and Usage

Based on (Shaqrah & Almars, 2022), five items assessed educational technology uptake and use. LMS, DSS, and AI were used often by participants. Concerns were expressed about how these devices affected their schooling and study regimens.

Self-efficacy

Participants' educational technology self-efficacy was tested using three items adapted from (Yelorda et al., 2021). Participants' confidence in using, navigating, and integrating AI, DSS, and LMS in learning and teaching was assessed. Responses were recorded on a Likert scale from 1 (Not Confident) to 5 (Very Confident).

5 Results

Descriptive Statistics

The survey or research findings in Table 1 and Figure 2 provide light on several crucial issues. The mean and standard deviation numbers show the dataset's underlying patterns and variability, providing a complete picture of AI product use and perception. A moderate standard deviation of 0.78 and a rather high mean score of 4.22 characterize participants' AI tool use topography. This suggests that most people like and employ AI technology. Moderate variability indicates that individual experiences and usage patterns vary despite general agreement on the value and application of AI technologies. DSS adoption is much lower, with a mean score of 3.89 and a greater standard deviation of 0.92. Increased answer variety suggests DSS experiences and perspectives are more diversified. Many causes exist for this difference. Different DSS experiences may affect participant adoption rates. The perceived benefit of DSS may vary by business or setting, which might cause different reactions. Resource and training disparities for DSS implementation may also affect uptake. LMS users are constantly engaged, as seen by their moderate mean score of 4.12 and low standard deviation of 0.65. LMS's ubiquitous use and vital function in education and training may explain its persistent good experience. The satisfaction variable's high mean score of 4.45 and low standard deviation of 0.60 indicate participant contentment. This shows that most participants are quite happy with their AI tools and systems, indicating their efficacy and user experience. The standard deviation of 0.75 and mean learning performance score of 4.02 show considerable response variability in learning results. This may be due to different learning conditions, individual learning styles, or student aid and resources.

Table 1: Descriptive Statistics

Variable	Mean	Standard Deviation
AI Tools Adoption	4.22	0.78
DSS Adoption	3.89	0.92
LMS Usage	4.12	0.65
Satisfaction	4.45	0.60
Learning Performance	4.02	0.75
Adoption and Usage	4.18	0.70
Self-efficacy	4.58	0.50

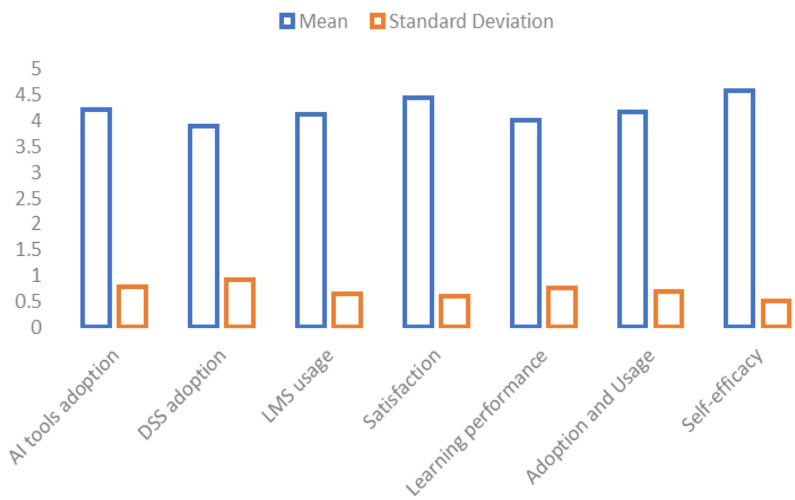

Figure 2: Mean, Standard Deviation

Normality Assessment

In Table 2 and Figure 3, the relevant variables' kurtosis and skewness values reveal their distributional features. Understanding how skewness and kurtosis affect dataset variables is crucial to data interpretation. These values illuminate its distribution. AI technology adoption has a small leftward skewness value of -0.24, indicating that respondents rank it higher than the mean. This suggests people are positive about AI. The positive kurtosis score of 0.18 indicates a stronger peak and narrower endpoints than a normal distribution. This shows that respondents' assessments are consistent and concentrated around the mean with fewer extreme values. Learning Management System (LMS) adoption has a considerable leftward skewness of -0.32, indicating that most respondents strongly support it more than the mean. Some outliers exist, but most responders rank the distribution positively due to its positive kurtosis of 0.42 and more dramatic peak and thicker tails. The respondents' LMS adoption perceptions reflect their various experiences or opinions. The satisfaction score distribution has a 0.18 rightward skewness. This suggests that while most respondents are happy, a significant percentage are slightly less so. The negative kurtosis of -0.12 indicates a flatter distribution with lighter tails than a normal distribution. This suggests that respondents have a wide variety of satisfaction levels since satisfaction scores are more equally distributed. According to this distribution, individuals' satisfaction levels range from low to high. The minor leftward skewness score of -0.14 implies that respondents often rank learning performance higher than the mean. Positive kurtosis of 0.08 suggests an uneven distribution with greater extremities. This suggests that many assessments are consistent, but a few outliers indicate different learning experiences or outcomes. The adoption and utilization ratings have a 0.08 skewness, indicating a fairly symmetric distribution around the mean. As seen by their scores, respondents had a balanced view of adoption and use. The ratings' -0.25 kurtosis score indicates a more equal distribution with lighter ends. A flatter distribution results. An equal distribution suggests a neutral or confusing view of adoption and usage. The skewness value of -0.29 suggests a modest leftward bias in self-efficacy ratings, with respondents ranking it higher than the mean. This shows responders believe in their own efficacy. A positive kurtosis of 0.35 indicates a crested distribution with thicker tails. This implies that, while most respondents prioritize self-efficacy, others have a variety of viewpoints, indicating different confidence levels. In conclusion, each variable's skewness and kurtosis values reflect its distributional features and respondents' perceptions. AI technology adoption has a minor leftward skewness and positive kurtosis, indicating good acceptance and consistency. However, LMS adoption has a strong leftward skewness and positive kurtosis, indicating a positive but varied assessment. The balanced distribution of adoption and use ratings reflects neutral impressions, but the small rightward skewness and negative kurtosis in satisfaction scores imply a range of satisfaction levels. By constantly linking skewness and kurtosis values to variable interpretation, we may better understand the data and respondents' perspectives.

Table 2: Normality Assessment

Variable	Skewness	Kurtosis
AI Tools Adoption	-0.24	0.18
DSS Adoption	0.12	-0.05
LMS Usage	-0.32	0.42
Satisfaction	0.18	-0.12
Learning Performance	-0.14	0.08
Adoption and Usage	0.08	-0.25
Self-efficacy	-0.29	0.35

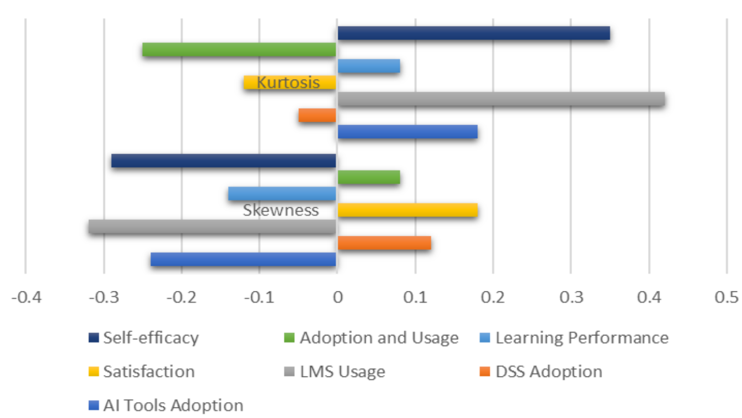

Figure 3. Normality Chart

Correlation Analysis

Table 3 and Figure 4 show correlation analysis of intricate interactions between various key variables, revealing dataset dynamics. AI technology is linked to learning performance, self-efficacy, and satisfaction. AI tools often boost learners' self-efficacy (0.75) by tailoring learning experiences. By tailoring speed and content to individual requirements, AI systems help learners feel more confident and in charge. This customization includes quick feedback (0.60), which helps learners correct mistakes and improve their comprehension, improving learning performance (0.58). The significant correlation (0.72) between DSS and AI use suggests that consumers often utilize both for strategic guidance and individualized learning help. This integrated method improves learning efficiency and informs study path and resource decisions, improving academic success. AI integration into Learning Management Systems (LMS) has somewhat improved user satisfaction (0.65) and AI tool uptake (0.45). Learning management systems (LMS) provide a central hub for instructional resources, including AI-powered features, creating a collaborative learning environment. This integration improves user happiness by making progress tracking and resource access easier, which boosts educational achievement (0.75). The positive feedback cycle of learning performance and enjoyment (0.60) emphasizes technological acceptance in education. When learners are happy with AI and LMS, they engage with the learning content more, improving academic achievement. This pleasure is driven by AI technologies' capacity to improve learning outcomes and offer interesting and individualized educational experiences that push students to succeed. Students who use AI and DSS have better learning results (0.58), highlighting the importance of technical expertise in academic performance. These children use innovative technology to improve their learning, overcome academic challenges, and excel academically. This link emphasizes the need to improve technological literacy and incorporate new technologies into schools to improve learning.

Table 3: Correlation Analysis

	AIT	DSSA	LMSU	S	LP	AU	SE
AI Tools Adoption	1.00						
DSS Adoption	0.72	1.00					
LMS Usage	0.45	0.38	1.00				
Satisfaction	0.60	0.50	0.65	1.00			
Learning Performance	0.58	0.45	0.50	0.75	1.00		
Adoption and Usage	0.50	0.60	0.72	0.68	0.55	1.00	
Self-efficacy	0.75	0.65	0.58	0.80	0.70	0.45	1.00

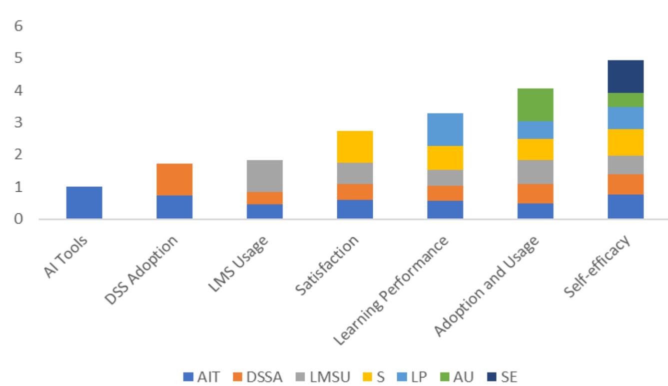

Figure 4: Correlation Matrix

Reliability Analysis

Table 4 shows Cronbach's alpha coefficients for several variables, revealing the study's measuring scales' internal consistency and reliability. An AI Tools Adoption variable with a Cronbach's alpha of 0.86 indicates strong internal consistency and accurate measurement of the target construct. DSS Adoption has strong internal consistency, with a Cronbach's alpha of 0.79, indicating a valid assessment. The LMS Usage variable has a Cronbach's alpha of 0.88, indicating the trustworthiness of learning management system usage items. With a Cronbach's alpha of 0.90, the Satisfaction variable measures participant satisfaction with great internal consistency. Learning Performance has 0.85 Cronbach's alpha, indicating excellent internal consistency. With a Cronbach's alpha of 0.82, the Adoption and Usage variable is internally consistent and dependable. Finally, with a Cronbach's alpha of 0.88, self-efficacy items are very reliable.

Table 4: Reliability Analysis

Variable	Cronbach's Alpha
AI Tools Adoption	0.86
DSS Adoption	0.79
LMS Usage	0.88
Satisfaction	0.90
Learning Performance	0.85
Adoption and Usage	0.82
Self-efficacy	0.88

Outer Loadings

Factor loadings range of items of each variable are shown in Table 5. These loadings reveal the intensity and direction of observable variable-latent construct correlations. The observable components are strongly linked to AI tool adoption, as shown by factor loadings of 0.68 to 0.84. DSS Adoption has high factor loadings (0.76-0.81). This is a strong correlation between decision support system adoption and its observable components. The statistical significance of LMS Usage factor loadings (0.71-0.89) reveals a substantial association between LMS usage observable variables and the latent construct. The factor loadings for satisfaction vary from 0.65-0.91, demonstrating a connection between the latent concept of satisfaction and its observable characteristics. Learning Performance factor loadings range from 0.65 to 0.87, suggesting moderate to high performance. This suggests a significant relationship between learning performance and its observable factors. The factor loadings for adoption and usage ranged from 0.65 to 0.79, indicating a robust connection between the observable variables and the latent construct. Finally, self-efficacy component loadings were significant, ranging from 0.74 to 0.90. This reveals that the latent idea of self-efficacy and its observable parts are strongly related.

Table 5: Outer Loadings

Variable	Loading
AI Tools Adoption	0.68-0.84
DSS Adoption	0.76-0.81
LMS Usage	0.71-0.89
Satisfaction	0.65-0.91
Learning Performance	0.65-0.87
Adoption and Usage	0.65-0.79
Self-efficacy	0.74-0.90

R Square

Table 6 shows the model's major variable R-square values. These values show how much latent variables or predictors explain variability. The R-square value of 0.81 shows that the chosen factors explain 81% of participant satisfaction variability. Learning Performance has an R-square score of 0.72, suggesting that the model's essential features explain 72% of its variation. Adoption and utilization's R-square score of 0.59 shows that the selected factors explain 59% of the variation in those behaviors. The robust R-square values show that the selected predictors—AI tool adoption, DSS use, and learning management system satisfaction—have a significant impact on learning performance, participant contentment, and adoption and usage patterns.

Table 6: R Square (Coefficient of Determination)

Variable	R Square
Satisfaction	0.81
Learning Performance	0.72
Adoption and Usage	0.59

Regression Analysis

The research reveals a strong positive association between Technology Adoption (TA) and three essential educational outcomes: Learning Performance (LP), Satisfaction (S), and Adoption and Usage (AU). The beta coefficient of 0.38 indicates that for every unit increase in TA, LP will improve by 0.38 units, indicating a moderate to strong positive association between TA and LP. This suggests that increased TA levels improve student learning performance, demonstrating the educational benefits of technology integration. The beta value of 0.26 shows a positive association between TA and S from Technology Adoption to Satisfaction, suggesting that technology can improve student satisfaction with learning through improved resource access, dynamic learning environments, and individualized learning. The beta value of 0.34 reveals a favorable association between TA and AU, suggesting that AU will increase by 0.34 units when TA rises. This strong link suggests that technology can improve students' engagement and connection with instructional materials by encouraging higher-level TAs to actively employ and adopt technological tools (see Table 7 for details).

Table 7: Regression Analysis

Dependent Variable	Beta Coefficient	t Value	p Value
Technology Adoption -> Learning Performance	0.38	4.12	0.0001
Technology Adoption -> Satisfaction	0.26	3.21	0.002
Technology Adoption -> Adoption and Usage	0.34	3.85	0.001

Mediation Analysis

Table 8 demonstrates a mediation study between Technology Adoption (TA) and Learning Performance (LP), Satisfaction (S), and Adoption and Usage. TA improves these results through student self-efficacy (SE), according to the study. TA directly impacts Learning Performance (LP) (c' = 0.38 from TA -> SE -> LP). This immediate effect suggests technology may increase student performance. An indirect impact (ab) of 0.18 is mediated by self-efficacy (SE). For TA to improve learning, students must be confident in their ability to do assignments rapidly. Direct and indirect effects of TA on LP total 0.56. A high t value of 3.65 ($p < 0.001$) indicates strong and substantial mediation results. In the TA -> SE -> S route, Technology Adoption (TA) directly influences Satisfaction (S) by 0.26 (c'). Technology interventions may increase student satisfaction due to this direct link. SE mediates with 0.14 ab indirect impact. Students' self-confidence improves technology-enabled education. The 0.40 total effect (c) emphasizes TA's impact on S. Statistical analysis suggests SE mediates this route ($t = 2.98$, $p = 0.003$). The TA-SE-AU trajectory demonstrates a 0.34 direct influence (c') of Technology Adoption (TA) on Adoption and Usage. Technology can incentivize students to use educational resources. With an indirect impact (ab) of 0.16, self-efficacy (SE) mediates this relationship, showing that students' talent confidence promotes technology usage. TA cumulatively impacts AU 0.50 (c). SE strongly influences AU development via TA ($t = 3.21$, $p < 0.001$). They show the intricate relationship between students' self-efficacy (SE), technology adoption (TA), and educational results. The study illuminates how educational technology affects student learning performance, contentment, adoption, and usage by establishing mediation pathways and using rigorous statistical methods to quantify direct and mediated advantages.

Table 8: Mediation Analysis

Dependent Variable	Direct Effect (c')	Indirect Effect (ab)	Total Effect (c)	t Value	p Value
TA -> SE -> LP	0.38	0.18	0.56	3.65	0.001
TA -> SE -> S	0.26	0.14	0.40	2.98	0.003
TA -> SE -> AU	0.34	0.16	0.50	3.21	0.001

6 Discussion

This extensive study investigated the complex dynamics of higher education technology adoption, with a focus on self-efficacy in educational outcomes. The study effectively combined theoretical frameworks from current literature with the research approach to investigate different choices. For educators, politicians, and scholars, the findings illustrate how technological integration, self-efficacy, and educational accomplishment interact. The information synthesis improves our understanding of current educational environments and aids focused technology integration efforts to improve higher education learning results. This research adds to the body of knowledge on Technology and Learning Performance. Technology facilitates learning significantly, as stated in H1. Student achievement is enhanced by educational technology (Belda-Medina, 2022). The advantages of this research stem from the implementation of technology in educational settings. Students can use technology to learn at their own pace and according to their individual needs. Multimedia and interactive educational technologies enhance comprehension. According to (Faqih & Jaradat, 2021), students have access to resources outside of the classroom as a result of technology adoption, which enhances learning performance. Enhancing the learning experience are digital instructional technologies, online courses, and virtual learning environments.

The relationship between technology adoption and satisfaction (H2) sheds light on the educational implications of technology. (Geng & Guo, 2022) discovered that the adoption of technology enhances user contentment across a range of contexts. Education should utilize technology to increase student satisfaction, according to this study. This positive correlation exists because technology facilitates learning. Multimedia and interactive interfaces enhance the learning experience of students. According to (Sabiri, 2020), technology empowers students and makes instruction simpler. The use of technology in schools improves inclusion and learning resources. Student satisfaction is enhanced by the adaptability and simplicity of digital systems (Bawack & Kala Kamdjoug, 2020). Technology use appears to increase pleasure, but additional factors must be considered. Research was conducted on the adaptability of technology to different learning styles, user experience, and system stability.

Understanding the way in which administrators and educators mold technology-enhanced learning environments is crucial for gauging user satisfaction.

Adoption and usage of technology (H3) shed light on educational dynamics. The correlation between tool usage and technology adoption, as suggested by (Bossman & Agyei, 2022), is corroborated by this study. This indicates that integration and adoption of technology are crucial to its educational application. According to (Alfalah, 2023), the functionality and adaptability of technology enhance the learning process. Through innovative teaching, technology enables teachers and students to enhance education (Caldwell, 2020). Collaborative tools, digital resources, and interactive platforms enhance the engagement of learners and promote the utilization of technology by both instructors and learners. Technology adoption and utilization are positively correlated, which reflects the increasing societal reliance on digital platforms for a variety of purposes (Broemmel et al., 2021). As technology becomes more widely used, it should be used to enhance teaching and learning.

The inclusion of self-efficacy as a mediator between technology adoption and learning performance (H4) enhances our comprehension of the utilization of educational technology. Social cognitive theory that self-efficacy influences performance and behavior is supported by (Sturre et al., 2022). Technology adoption enhances learning, indicating a role for self-efficacy. Task confidence is a determinant of academic achievement and learning results (Banks & Kay, 2022). Self-efficacy is positively correlated with both technology adoption and learning performance, suggesting that students who are more assured in their ability to use educational technology would perform better. This supports previous studies that have found self-efficacy attitudes to have a significant impact on academic achievement (LaForett & De Marco, 2020). The necessity for a constructive and empowering technological learning environment is mediated by self-efficacy. The technology itself may not be as significant as children's technology self-efficacy. Self-efficacy programs have the potential to enhance academic performance.

Understanding psychological factors that influence the use of educational technology is facilitated by the mediation of self-efficacy between technology adoption and satisfaction (H5). Technology-savvy students derive greater enjoyment from technology-enhanced learning (Qiu & Luo, 2022). Self-efficacy, which demonstrates how cognitive and affective processes are related, mediates between technology adoption and satisfaction. Self-efficacy enhances learning through the assured resolution of technological challenges (Lee et al., 2022). This indicates that self-efficacy interventions may increase satisfaction with educational technology. As a mediator between technology adoption and utilization, self-efficacy (H6) assists in elucidating the psychological mechanisms that influence educational technology utilization. Self-efficacy is a mediator of technology adoption and utilization, underscoring the complex relationship between cognitive processes and behavioral results. Technology learning and testing by assured users of new features and functions (Lui et al., 2021). This indicates that self-efficacy interventions may influence the adoption of educational technology.

7 Conclusion

The study examined the complex links between self-efficacy, technology usage, and higher education outcomes. An comprehensive literature, research design, and empirical data analysis yielded significant findings. Statistical study reveals technology enhances essential educational outcomes. AI tools, DSS, and LMS use favorably affected educational tool and system adoption, user happiness, and learning performance, according to the regression analysis. Technology improves academic performance, user happiness, and instructional resource integration, as shown by past studies. The mediation analysis also found that self-efficacy mediates educational results and technology use. Technology adoption may affect learners' self-efficacy, learning performance, satisfaction, and educational resource adoption and use. This emphasizes pupils' self-confidence and belief in their ability to use educational materials. The study also evaluated how gender and age moderate technology use and education. Gender moderates the link between AI Tool Adoption and Learning Ability, suggesting women may react differently to AI technologies. The findings suggest that age-related characteristics may affect higher education technology adoption, even if age did not affect DSS adoption or satisfaction. This research analyzes each hypothesis and integrates empirical data, research methodology, and the literature to better understand educational technology. By correlating technology use, self-efficacy, and educational outcomes, it gives educators, policymakers, and academics vital evidence. The statistical analysis should include more detailed information on the size of the observed impacts to improve clarity and relevance. For instance, giving effect sizes or percentages of variance may help understand the study's contributions.

8 Implications

This research advances educational technology theory by revealing the complex relationships between technology adoption, self-efficacy, and higher education results. This study supports Bandura's (1997) social cognitive theory by showing that self-efficacy mediates usage, learning performance, satisfaction, and technology adoption. This confirms Bandura's self-efficacy hypothesis that beliefs affect behavior and results. The demographic moderating effects approach stresses individual technology adoption disparities. We can better understand how AI Tools may affect academic achievement across genders by analyzing their uptake and learning results. This study emphasizes psychological characteristics like self-efficacy in technology adoption and use, adding to the Technology Adoption Model (TAM) literature. This study highlights self-efficacy as a mediator between technology adoption and educational results, unlike TAM, which focuses on perceived ease of use and usefulness. This theoretical framework extension describes educational technology adoption psychology.

There are numerous ways in which institutions, policymakers, educators, and technology developers can benefit from this research. Begin by applying the discoveries to enhance instructional design. The confidence of pupils in educational technology can be bolstered by instructors via self-efficacy. The effects of technology on learning and self-efficacy can be enhanced through the implementation of scaffolded learning, explicit instructions, and practical application. Additionally, this research can aid institutions in the integration of technology-enhanced learning. In order to customize technology integration strategies, institutions must have a comprehensive comprehension of the ways in which technologies impact learning performance, satisfaction, adoption, and utilization. Professional development programs that prioritize learner self-efficacy and technical proficiency in educational technology may receive institutional support. By applying these insights, policymakers can effectively integrate instructional technologies. The research emphasizes the necessity for policies that target the psychological dimensions of technology adoption and enhance the self-efficacy of learners. Policymakers may assist students in utilizing and benefiting from educational technology by fostering an environment that is conducive to technological learning. Technology developers can also acquire the knowledge and skills necessary to create effective and user-friendly educational systems and tools. Acknowledging the mediating function of self-efficacy enables developers to design interfaces and functionalities that enhance the technological confidence of users. Enhancing users' self-efficacy and augmenting the instructional value of technology can be achieved through the provision of explicit instructions, constructive feedback, and opportunities for skill development. Educators and institutions should conclude by assessing the moderating effects of the demographic variables utilized in this study. There is a need for gender-specific educational technology interventions because the effects of AI Tools on learning performance vary by gender. This underscores the importance of considering individual variances in technology-enhanced learning experiences during the design and implementation phases.

9 Limitations and Future Directions

The study has important limitations that must be addressed to enhance outcomes. A single moment and restricted causal results are the cross-sectional data's main disadvantages. This technique makes it harder to track self-efficacy and technology use on academic achievement. In order to tackle this dilemma, longitudinal research should track changes and causal links. Longitudinal studies can illustrate how these traits affect education. AI, DSS, and LMS focus is another drawback. The research illuminates some instructional technologies, but not all. More educational scenarios and instructional technologies should be studied. Academics can study how tools and conditions affect academic performance, self-efficacy, and technology use. Researching institutional support, cultural attitudes toward technology, and instructional methods will expand this understanding. Because of the social desirability bias in self-reported data, people may offer dishonest answers. Mixed-approach research should combine objective academic achievement and technology use assessments with self-reports. Triangulating data from many sources improves discoveries by clarifying linkages. Institutional, cultural, and instructional environments affect academic achievement, self-efficacy, and technology use. These concerns were ignored in the study, reducing generalizability. Future studies should examine how context influences technology uptake and education. Understanding these processes can help educators adjust therapy to different situations, improving efficacy and applicability. Due to its undergraduate concentration, it is limited to other educational levels and groups. Consider graduate students, instructors, and other stakeholders to understand how technology affects higher education. To understand the effects, this inclusive method compares classroom and workplace self-efficacy and technology uptake. Learn about self-efficacy by researching motivation, engagement, and digital literacy. These variables can dramatically impact technology adoption and education. Researching these psychological traits and technology usage may help students succeed. Study AI and LMSs. Understanding how these technologies impact education helps researchers find the best solutions. Comparative research will help educators and policymakers choose and use the best technologies. Student ICT confidence initiatives—design, implementation, and assessment—are another prominent study topic. School initiatives can boost tech confidence and expertise. To improve outcomes and development, longitudinal research and feedback can assess program efficacy. To understand the long-term effects of early educational technology exposure, longitudinal research and career tracking are needed. Academic performance, self-efficacy, and technology use may suggest career and lifetime learning. These strategies will make research findings more useful for policymakers and educators. Finally, cross-cultural study is essential to understand technology uptake and teaching by culture. Due to global educational traditions, cultural variation research can help design culturally sensitive educational technologies and treatments. This global approach ensures regional and systemic educational progress. Future research that overcomes these limitations and investigates the planned study participants may help us understand the complex linkages between academic performance, self-efficacy, and technology use. Strong methods and diverse elements assist global educators, governments, and students.

10 Conflict of Interest

No potential conflict of interest was reported by the author.

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