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Research Article

AI and big data-driven decision support for fostering student innovation in music education at private underground colleges

Liu Liu[1*]

[1] Krirk University, Bangkok, 10220, Thailand
*** Corresponding Author:** 1968016338@qq.com

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ABSTRACT

This study investigates the transformative impact of AI-based Decision Support Systems (DSS) and Big Data Analytics (BDA) on student innovation and employability skills in an era of rapid technological advancement, with a focus on the mediating role of technological acceptance and the moderating role of resource availability. This study, which draws on a wide range of educational contexts and data sources, gives complete knowledge of the complex links between technology adoption, student results, and contextual factors. The results of this study show how AI-based DSS and BDA have a significant impact on musical education. These technological advancements enable tailored instruction and foster students' creative thinking. In order to prepare students for a work market that is rapidly changing, they act as a catalyst for improving employability skills. The study, however, emphasizes the complicated dynamics at work. Technological Acceptance emerges as a major mediating component, underlining the significance of students and instructors freely and effectively accepting technological tools. Furthermore, as a moderating factor, Resource Availability takes center stage, emphasizing the need for equitable access to educational resources to ensure that technology-driven advantages are accessible to all. The results of this study have broad repercussions. The adoption of AI and BDA by educational institutions is encouraged as transformative technologies for enhancing the learning process. Policymakers must create regulations that support equal access to technology and promote an innovative culture in the classroom. This study highlights for students how important it is to adopt new technologies, realizing how important they are in determining both their academic and career paths.

Keywords: AI-based Decision Support Systems, Big Data Analytics, Student Innovation, Employability Skills, Technological Acceptance, Resource Availability.

INTRODUCTION

Big Data Analytics (BDA) and AI-based Decision Support Systems (DSS) are transforming education by radically altering how teaching and learning are carried out. Due to the tailored learning opportunities, they offer, these technologies have a significant impact on education. AI-based DSS assesses each student's unique data to personalize resources and recommendations, increasing engagement and performance (Li et al., 2020). Additionally, data-driven decision-making tools help instructors track student achievement, improve educational methods, and simplify administrative responsibilities. The ability of AI to recognize problematic pupils makes early intervention possible, enabling prompt support and enhancing general student well-being. AI-powered features that adapt to various learning needs boost accessibility (Retico et al., 2021). With personalized content recommendations based on student preferences and performance, adaptive learning paths that dynamically modify difficulty, and intelligent tutoring systems that provide in-the-moment support, AI-powered features are revolutionizing education. Natural language processing assists language learners with grammar, vocabulary, and pronunciation, while automated grading and feedback save educators time and stimulate student growth. Learning is made more interesting through gamification and simulations, virtual labs provide hands-on practice, and sentiment analysis improves emotional support

(Craigon et al., 2023). Nonetheless, AI-based DSS and BDA are poised to play a growing role in influencing the future of education, providing chances to improve learning outcomes, increase efficiency, and encourage lifelong learning.

BDA and AI-based DSS have a significant impact on student innovation and employability skills in the educational environment. By giving students access to huge information and insights, these tools encourage innovative thinking among students, enabling them to investigate original solutions to practical problems (Al Ghatrifi, Al Amairi, & Thottoli, 2023). The culture of innovation that AI and BDA foster directly supports the development of employability skills like critical thinking, creativity, and problem-solving, all of which are highly prized in the labor market. Additionally, the tailored learning opportunities made possible by these technologies allow students to focus on their areas of interest and strength, which improves self-directed learning, a crucial employability skill (Bag, Pretorius, Gupta, & Dwivedi, 2021). Another important aspect of AI and BDA's influence is the ability to make data-driven decisions, which provides students with the skills needed to approach difficulties with informed choices. Employees who can use data to make decisions are valuable assets to firms, therefore data literacy directly translates into employability skills (Ashaari, Singh, Abbasi, Amran, & Liebana-Cabanillas, 2021). Furthermore, AI and BDA improve cooperation and interpersonal skills by facilitating collaboration and communication through virtual platforms. Students also receive practical experience by working on real-world projects, which is a vital asset for future employment. Finally, exposure to AI and BDA fosters adaptability and a dedication to lifelong learning, ensuring that students are well-prepared for a dynamic and technologically-driven work market (Dwivedi et al., 2023). By offering individualized advice, data-driven insights, and collaborative opportunities, AI-based decision support systems have the potential to have a substantial impact on student creativity. These platforms recognize students' distinct interests and strengths, personalizing learning routes and linking them with mentors and peers who share their innovative goals (Ashaari et al., 2021). AI is also essential for speeding up research and project management, allocating resources optimally, and detecting and assisting at-risk pupils. AI-driven Decision Support Systems enable students to develop their creative potential, engage in meaningful projects, and contribute to the advancement of new solutions across multiple fields by cultivating an atmosphere conducive to innovation.

In order to provide a comprehensive knowledge of their combined effects, it is important to understand how technological acceptance concurrently mediates the relationship between AI and BDA and how resource availability moderates it (Lyons-Burney & Godby, 2023). Second, the generalizability of findings is limited by the underexplored contextual variances across various educational levels and cultural contexts. It is crucial to look into how these technologies impact innovation and employability skills in many contexts (Chou, Shen, Shen, & Shen, 2023). Furthermore, many researchers rely on cross-sectional data, which lacks a longitudinal perspective. Longitudinal studies could shed light on AI and BDA's long-term consequences, highlighting their dynamic nature. Another gap is improved measurement tools and metrics, as precise assessment methods are required to effectively estimate the impact of technologies (Lytras, Lytra, & Lytras, 2021). It is critical for schools and businesses to investigate specific employability skills influenced by AI and BDA, such as digital literacy and data analysis. Furthermore, the impact of Resource Availability differs between circumstances, as do the ethical and privacy concerns related to AI and BDA, as well as their potential influence on acceptance (Mark, 2019). Filling these research gaps will lead to a better understanding of the complicated links between technology adoption, innovation, employability skills, and educational resources.

The purpose of this study is to thoroughly examine how student innovation and employability skills are impacted by AI-based decision support and big data analytics in educational environments. This study aims to investigate how the links between these technologies and student outcomes are affected by the mediating function of technological acceptance and the moderating role of resource availability. The study aims to provide significant new insights into the dynamics of technology adoption, the impacts it has on innovation and employability, and the contextual factors that affect these interactions by concentrating on this objective. The following are the study's objectives:

To examine the influence of AI-based Decision Support on Student Innovation and Employability Skills among music students.

To investigate the effect of Big Data Analytics on Student Innovation and the enhancement of Employability Skills in music educational environments.

To explore the mediating role of Technological Acceptance in the relationships between AI-based Decision Support and both Student Innovation and Employability Skills, as well as between Big Data Analytics and Student Innovation and Employability Skills of music students.

To examine the moderating role of Resource Availability in the impact of AI-based Decision Support on Student Innovation and Employability Skills of music students.

To investigate how Resource Availability moderates the relationships between Big Data Analytics and both Student Innovation and Employability Skills in music educational settings.

This study has far-reaching ramifications for different stakeholders throughout the educational sector and society as a whole. The research addresses the crucial need for educational enhancement in the digital age, providing insights into how AI-based Decision Support and Big Data Analytics might transform learning experiences. The findings not only contribute to data-driven decision-making in education but also guide institutions and policymakers in optimizing resource allocation to realize the full potential of new technologies. The report also emphasizes how vital it is to give students the employability skills they will need for their future employment in order to increase their competitiveness in a labor market that is continually changing. It provides students with significant insights about the role of technology in their learning path, emphasizing the importance of adjusting to new tools. Employers gain from understanding how graduates who have worked with AI and BDA have a competitive advantage in a data-driven workplace. Policymakers can use the findings of the study to develop policies that promote innovation and fair access to educational resources. On a larger scale, the research contributes to societal progress by preparing a workforce that is not only technologically adept but also capable of driving economic growth, innovation, and global competitiveness. In essence, the study's significance extends beyond academia, shaping the future of education, technology adoption, employability, and societal well-being.

LITERATURE REVIEW

AI-Based Decision Support and Student Innovation

Artificial Intelligence-based DSS have changed how teaching and learning are done in the field of education. This paper explores the impact of AI-based DSS on student innovation, illuminating the ways in which these tools support and encourage students' innovative thinking. These technologies provide individualized recommendations and insights within educational environments and are powered by machine learning and data analytics (Liu, Chang, Forrest, & Yang, 2020). AI-based DSS stimulates the personalization of learning experiences by customizing learning materials to individual needs and preferences, establishing a sense of ownership over one's education, and inspiring students to experiment and invent. Furthermore, AI-powered platforms frequently confront students with real-world issues and offer assistance and resources while they search for solutions (Bertl, Ross, & Draheim, 2023). Critical thinking, inventiveness, and creative problem-solving abilities are fostered by this method. The data-driven feedback offered by these systems enables students to self-assess and make required adjustments, so encouraging ongoing progress and innovation (Shiang, Garwood, & Debenedectis, 2022). Furthermore, AI can enhance collaborative learning experiences by connecting students with classmates who have similar interests or projects, which can drive creativity as students share ideas and viewpoints. While AI-based DSS have a tremendous deal of potential to encourage student innovation, they also present significant difficulties and worries. To protect privacy and build trust, ethical issues related to the gathering and use of student data must be taken into account. The digital divide also presents a problem since uneven access to AI technology may limit innovation for some pupils and widen educational gaps (Tan, Lee, & Lee, 2022). Future studies should examine the long-term impacts of AI-based DSS on students' creative potential and job aspirations. The ethical ramifications of AI in innovation and education should also be covered. Strategies for ensuring fair access to AI technologies and new opportunities should also be investigated (Füller, Hutter, Wahl, Bilgram, & Tekic, 2022). Finally, AI-based Decision Support Systems have the potential to transform education by encouraging student innovation through personalization, problem-solving assistance, data-driven insights, and collaborative opportunities. While there are obstacles, continuing to explore these technologies in educational settings offers great prospects for developing the next generation of innovative thinkers and problem solvers.

H1: AI-based decision support has a significant and positive impact on student innovation.

AI-based Decision Support and Employability Skills

AI has quickly impacted the educational landscape, bringing about seismic shifts in the knowledge and abilities that students gain (Hua Hu, 2023). This study of the research explores how AI-based DSS affects and supports students' development of employable skills. One of the most important effects of AI-based DSS on employability skills is their function in improving students' technical proficiency. AI technology has grown essential in a wide range of areas, including healthcare and banking (Yigitcanlar et al., 2020). Students who are exposed to AI-based DSS gain technical skills and knowledge that are increasingly in demand in today's employment market (Shaik et al., 2023). Additionally, AI-based DSS supports students' growth in data literacy abilities. Students working with these systems engage in data analysis, interpretation, and insight extraction because AI heavily relies on data, which is a crucial skill for being employable in the data-driven workforce (Chatterjee, Chaudhuri, Vrontis, & Jabeen, 2022). AI-based DSS enhances critical thinking talents in addition to technical and data-related capabilities. Students are frequently required to critically assess information and make judgments in these systems (Shiang et al., 2022). This exposure promotes the development of critical thinking skills, which employers strongly respect. Adaptability is another important employability skill fostered by AI-based DSS. AI technologies are dynamic and always changing, and students who are exposed to them gain adaptability and a willingness to learn new technologies, which is a valuable asset in an ever-changing job landscape (Mohamed El Abd, 2023).

H2: AI-based decision support has a significant and positive impact on employability skills.

Big Data Analytics and Student Innovation

BDA in education refers to the systematic study of large amounts of data from various educational sources in order to reveal hidden patterns and insights that aid decision-making and improve educational processes (Marchena Sekli & De La Vega, 2021). Through numerous fundamental methods, this transformative technology plays a critical role in stimulating student innovation. To begin with, BDA promotes individualized learning by adapting instructional content to specific student needs and preferences, fostering a sense of ownership over their educational journey and instilling a predisposition for inquiry and invention (Peterson, 2018). According to Schmitt, (2023), BDA provides educators and students with data-driven insights that enable them to make wise decisions, adapt to changing situations, and stimulate innovative thinking and problem-solving. Students can explore topics of personal interest and apply their creative solutions to real-world problems because of BDA's personalization features, which foster inventive thinking (Ahaidous, Tabaa, & Hachimi, 2023).

H3: Big Data Analytics has a significant and positive impact on student innovation.

Big Data Analytics and Employability Skills

Across many industries, BDA has found its way into the workforce, changing the skill sets required to be employable. BDA entails the systematic study of large datasets in order to extract useful insights that can be used to improve decision-making processes (Li, Lin, Ouyang, & Luo, 2022). The impact of BDA on employability skills becomes clear as firms increasingly embrace data-driven strategies. One significant influence is the growth of data literacy abilities among employees, which allows them to read, interpret, and manipulate data competently (Shahbaz, Gao, Zhai, Shahzad, & Hu, 2019). The capacity to harness data has become a critical talent in a variety of work areas. BDA also promotes analytical thinking by requiring staff to deconstruct large statistics, uncover patterns, and generate actionable insights (Ezerins, Ludwig, O'Neil, Foreman, & Açıkgöz, 2022). This analytical attitude has evolved as a fundamental component of employability, allowing for critical decision-making processes (Ardagna, Bellandi, Damiani, Bezzi, & Hebert, 2021). Digital literacy is a requirement for using BDA tools and technologies, therefore being proficient in their use has become a necessary skill in the labor market today. Additionally, BDA encourages the growth of strong communication abilities, particularly when it comes to converting complex data discoveries into useful recommendations.

H4: Big Data Analytics has a significant and positive impact on employability skills.

Technological Acceptance as a Mediator

Technological Acceptance serves as a crucial mediator in the relationship between AI-based DSS and student innovation. It frequently results in more successful use of these systems when students and educators have a positive tendency to embrace and use AI-based DSS (Ho, Mantello, & Ho, 2023). This encouraging acceptance makes it easier to include AI-based DSS into the educational process, providing students with insightful information and individualized help that fosters an innovative environment (Kamble, Gunasekaran, Kumar, Belhadi, & Foropon, 2021). Positive technological acceptance has a variety of advantages. It promotes active participation with AI-based DSS, cultivates a sense of ownership over one's learning experience, and frequently ignites students' inventive thinking (Khan, Jabeen, Mehmood, Ali Soomro, & Bresciani, 2023). Additionally, by adapting learning experiences to individual needs and preferences, it enables the efficient use of personalized recommendations and insights, pushing students to explore and develop in areas of personal interest (Yao, Wang, Jiang, Li, & Li, 2022). Additionally, a favorable attitude toward technology enables users to exploit data-driven insights for creativity and decision-making (Koedinger et al., 2012). The preparedness of employees to adopt and effectively use technology in their professional positions is referred to as technological acceptance. It is an important component in determining how well AI-based DSS contributes to skill development. Employees' willingness to embrace and integrate AI-based DSS into their daily work routines indicates good acceptance (Alshahrani, Mohamed, Mukhtar, & Mokhtar, 2023). Employees are more inclined to fully utilize these systems in such instances. They actively engage with technology, looking for ways to use AI-driven insights and recommendations (Ho et al., 2023). This favorable acceptance serves as a driver for the development of employable skills, as employees actively work to improve their technical proficiency, data literacy, analytical thinking, problem-solving abilities, and adaptability. The mediating role of Technological Acceptance between Big Data Analytics (BDA) and Student Innovation is crucial in understanding how the acceptance of technology influences innovative thinking among students. Positive technological acceptance facilitates the development of this connection. The door is opened for BDA to improve students' educational journeys when they quickly adopt and integrate BDA technologies into their learning experiences (Cui et al., 2021). Students can actively participate with BDA by adopting data-driven insights and tailored learning when there is positive acceptance of the technology. This in turn fosters an environment where students can innovate (Kahveci, Alkan, Ahmad, Ahmad, & Harrison, 2022). Their capacity to think creatively and invent is enhanced when they use the power of BDA for informed decision-making and personalized discovery. Moreover, the mediating role of Technological Acceptance in the relationship between BDA and Employability Skills is central to understanding how technology acceptance influences the development of skills crucial for success in the workforce. This interaction is made possible by positive technological acceptance. The efficient use of BDA is made possible when workers quickly accept and incorporate BDA tools into their professional tasks (Alshahrani et al., 2023). Employees are given the freedom to actively engage with BDA thanks to this positive acceptance, which enables them to take advantage of data-driven insights, improve technical proficiency, cultivate data literacy, encourage analytical thinking, and fortify problem-solving skills all crucial elements of employability skills (Chou, Horng, Liu, Yu, & Kuo, 2022).

H5: Technological acceptance mediates the relationship between AI-based decision support and student innovation.

H6: Technological acceptance mediates the relationship between AI-based decision support and employability skills.

H7: Technological acceptance mediates the relationship between Big Data Analytics and student innovation.

H8: Technological acceptance mediates the relationship between Big Data Analytics and employability skills.

Resource Availability as a Moderator

The availability of resources can have a considerable impact on the amount to which AI-based DSS helps student creativity. When educational institutions have innovative technology, skilled support staff, and financial investments, AI-based DSS can boost student innovation (Wan et al., 2023). Students can benefit from innovative AI tools, personalized support, and enhanced learning experiences that stimulate creative thinking in resource-rich environments. AI-based DSS may have less of an impact on student innovation in settings with limited resources due to limited access to AI technologies and resources (Gaglianese, Forti, Paganelli, & Brogi, 2023). Students in these conditions may struggle to effectively exploit AI tools, which may limit their innovation. The moderating effect of Resource Availability stresses the importance of equitable access to resources to maximize the innovative potential of AI-based DSS in education. (Vincent-Lancrin, Urgel, Kar, & Jacotin, 2019). Furthermore, the availability of resources is also important in modulating the relationship between AI-based DSS and the development of employable skills. Organizations and educational institutions with abundant resources can invest in comprehensive AI solutions, training programs, and support systems that enable employees and students to effectively exploit DSS (Wang, Sun, & Chen, 2023). Given that people have access to the required tools and training, resource availability in this case promotes the development of employability skills including technical competence, data literacy, and problem-solving. Contrarily, in environments with limited resources, the ability of AI-based DSS to develop these abilities may be hampered, which could have an influence on employability (Jokhan et al., 2022). BDA can be used widely at resource-rich educational institutions to analyze large datasets, tailor learning experiences, and give students with data-driven insights (Pratsri, Nilsook, & Wannapiroon, 2021). Students have access to and use BDA tools to stimulate innovative thinking in such situations, where financial and technological resources are available. Organizations and educational institutions with ample resources can invest in robust BDA infrastructure, training programs, and support systems to improve the abilities of employees and students (Bhunia & Chatterjee, 2023). BDA can effectively encourage employability skills like data literacy, critical thinking, and flexibility in situations with abundant resources. However, the potential for skill development is curtailed in resource-poor situations where access to BDA technologies and training is confined (Kusi-Sarpong, Orji, Gupta, & Kunc, 2021). As a result, the availability of resources is a key moderating factor in deciding how BDA affects employability skills.

H9: Resource availability moderates the relationship between AI-based decision support and student innovation.

H10: Resource availability moderates the relationship between AI-based decision support and employability skills.

H11: Resource availability moderates the relationship between Big Data Analytics and student innovation.

H12: Resource availability moderates the relationship between Big Data Analytics and employability skills.

Based on the above discussion and literature, we developed the following conceptual framework shown in **Figure 1**.

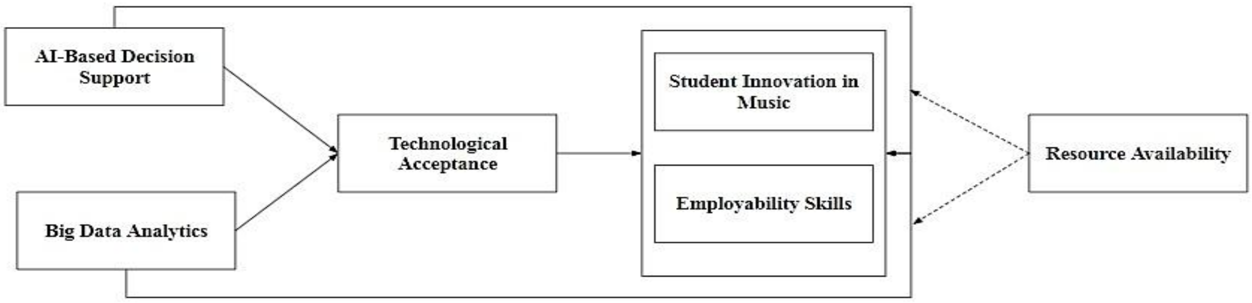

Figure 1. Conceptual Framework

METHODOLOGY

For this study, a quantitative research design was employed to investigate the impact of AI-based Decision Support and Big Data Analytics on Student Innovation and Employability Skills among music college students. The target population encompassed music college students, and a sample size of 375 individuals was randomly selected from various music colleges, ensuring diversity and representativeness. Data collection involved the distribution of structured survey questionnaires, utilizing Likert-type scales to measure constructs related to AI-based Decision Support, Big Data Analytics, Technological Acceptance, Resource Availability, Student Innovation, and Employability Skills. Ethical guidelines were strictly followed, with informed consent obtained from all participants to ensure their voluntary participation and the confidentiality of their responses.

The collected data were analyzed using SmartPLS 4 software, which enabled the application of Structural Equation Modeling (SEM) techniques. The analysis included both the measurement model (confirmatory factor analysis) and structural model (path analysis) assessments to explore the intricate relationships between the studied variables. To enhance data validity and reliability, the survey instruments were pre-tested for clarity and appropriateness with a smaller sample of students before the main data collection. Internal consistency measures such as Cronbach's alpha and composite reliability were used to assess the reliability of the constructs.

FINDINGS

Table 1 and **Figure 2** provide valuable insights into the construct reliability and validity analysis carried out for several key constructs in this research study, including AI

Based Decision Support (AIBDS), Big Data Analytics (BDA), Employability Skills (ES), Resource Availability (RA), Student Innovation (SI), and Technology Acceptance (TA). Upon interpreting the table in light of the established cutoff values, a number of noteworthy findings emerge. First off, the Outer Loading values which indicate how strongly items are related to their respective constructs are typically extremely reliable, with the majority above the widely used limit of 0.7. This implies that these items effectively measure the constructions for which they were designed. Second, information about multicollinearity among items inside each construct is provided by the VIF (Variance Inflation Factor) values. It is important to notice that none of the VIF values surpass the widely accepted thresholds of 5 or 10, indicating that there are no significant issues with item redundancy or overlap. Additionally, the internal consistency reliability scores, or Cronbach's Alpha values, are remarkably high, with many constructs exceeding the generally accepted limit of 0.7. This demonstrates that the elements inside each construct consistently measure the same underlying concept, assuring the measurement equipment' dependability. Another indication of construct reliability, CR (Composite Reliability) values show strong dependability as well, regularly above the ideal cutoff of 0.7 or 0.8 for all constructions. Finally, for all constructions, the AVE (Average Variance Extracted) values are comfortably over the recommended cutoff of 0.5 or 0.6, showing that the items successfully capture the variance within their respective constructs.

Table 1. Construct Reliability and Validity

	Items	Outer Loading	VIF	Cronbach's Alpha	CR	AVE
AI-Based Decision Support	AIBDS1	0.815	2.185	0.832	0.881	0.597
	AIBDS2	0.733	1.636			
	AIBDS3	0.737	1.753			
	AIBDS4	0.814	1.931			
	AIBDS5	0.759	1.470			
Big Data Analytics	BDA1	0.833	2.849	0.868	0.903	0.613
	BDA2	0.808	2.780			
	BDA3	0.854	2.963			
	BDA4	0.864	3.196			
	BDA5	0.745	1.615			
	BDA6	0.551	1.244			
Employability Skills	ES1	0.820	2.497	0.942	0.953	0.743
	ES2	0.843	2.985			
	ES3	0.892	4.358			
	ES4	0.893	4.069			
	ES5	0.868	3.572			
	ES6	0.832	3.803			
	ES7	0.883	5.018			
Resource Availability	RA1	0.911	2.616	0.849	0.908	0.768
	RA2	0.835	1.911			
	RA3	0.881	2.064			
Student Innovation	SI1	0.926	4.083	0.936	0.954	0.838
	SI2	0.922	3.896			
	SI3	0.906	3.351			
	SI4	0.908	3.180			
Technology Acceptance	TA1	0.809	1.755	0.834	0.889	0.668
	TA2	0.771	1.597			
	TA3	0.838	1.945			
	TA4	0.849	2.027			

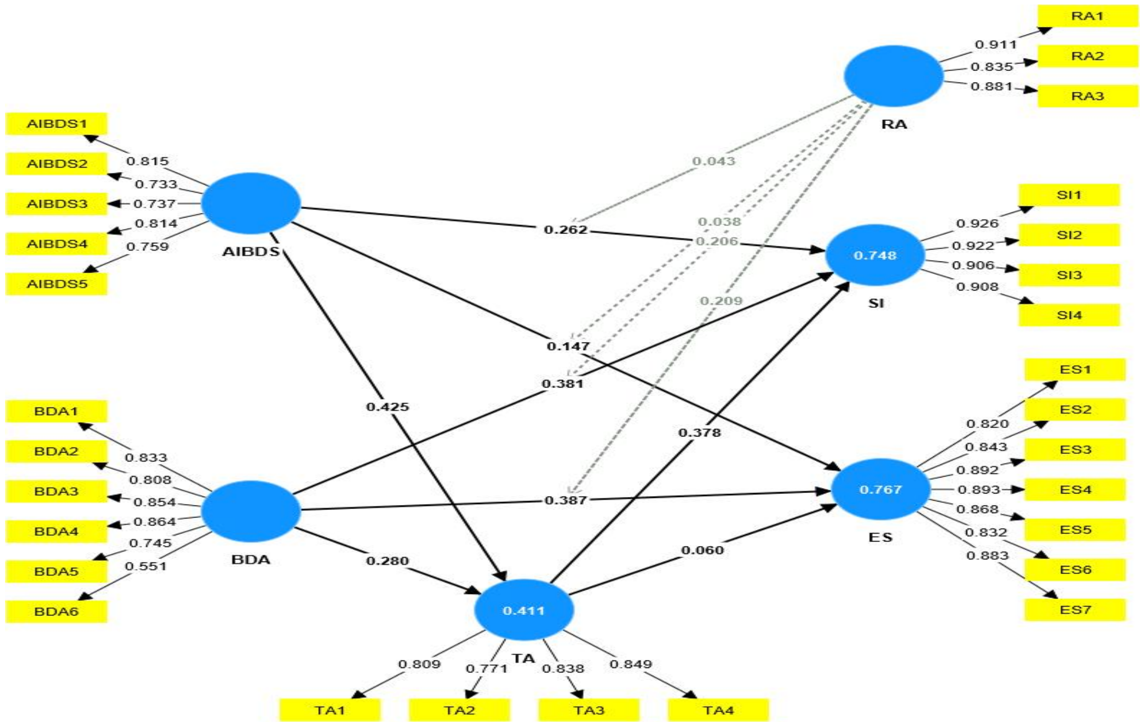

Figure 2. Measurement Model

The findings of a Discriminant Validity study using the Heterotrait-Monotrait (HTMT) ratio are presented in **Table 2**. This is an important assessment to ensure that the various constructs under research are unique and do not overlap significantly in their measurement. Each cell in the table displays the HTMT ratio between two constructs, with lower values indicating stronger discriminant validity. The diagonal elements of Table (AIBDS, BDA, ES, RA, SI, and TA) are all set to 1 as a starting point because a construct should be precisely connected to itself. Second, the off-diagonal parts of the table contain the HTMT ratios between pairs of constructs. Notably, the majority of these values are under 1, indicating the notions' great discriminant validity. The HTMT ratio between AIBDS and BDA is 0.733, indicating that these two constructs are clearly separate and do not have considerable measurement overlap. Also supporting the notion that Employability Skills (ES) and Resource Availability (RA) are distinct notions is the HTMT ratio of 0.859 between ES and RA. The lowest HTMT values, such as 0.417 between SI and AIBDS, suggest a high level of discriminant validity, confirming the distinction between Student Innovation (SI) and AI-Based Decision Support (AIBDS).

Table 2. Discriminant Validity (HTMT)

	AIBDS	BDA	ES	RA	SI	TA
AIBDS						
BDA	0.733					
ES	0.456	0.797				
RA	0.542	0.629	0.859			
SI	0.417	0.778	0.885	0.800		
TA	0.710	0.639	0.668	0.836	0.781	

Note: AIBDS=AI Based Decision Support, BDA=Big Data Analytics, ES=Employability Skills, RA=Resource Availability, SI=Student Innovation, TA=Technology Acceptance.

Table 3 and **Figure 2** show the coefficients of determination as R-squared values, as well as modified R-squared values for key constructs in a statistical model. These stats are crucial for determining how well the independent variables in the model explain the variation in the dependent variables. The R Square column reveals that the R-squared value for Student Innovation is 0.748. This value indicates that the independent factors included in the model account for roughly 74.8% of the variance in student innovation. The R-squared value for employability skills is 0.767, indicating that the independent variables included in the model explain around 76.7% of the variance in employability skills. The R-squared value for technological acceptance is 0.411. This means that the independent variables in the model can explain roughly 41.1% of the variance in Technological Acceptance.

Table 3. Coefficient of Determination

	R Square	R Square Adjusted
Student Innovation	0.748	0.744
Employability Skills	0.767	0.763
Technological Acceptance	0.411	0.407

Table 4 and **Figure 3** provide critical information regarding the path coefficients, T-values, and P-values within a structural equation model, offering light on the variables in the study. The quantitative estimates of the intensity and direction of these interactions are provided by these path coefficients. AIBDS has a positive influence on SI, as indicated by the path coefficient of 0.262. Additionally, the extremely low P-value of 0.000 and the high T-value of 5.666 show that this association is statistically very significant, pointing to a solid and significant link between AI-based decision help and student innovation. Similarly, with a path coefficient of 0.147, the path from AIBDS to Employability Skills (ES) demonstrates a favorable influence. The statistical importance of this association is shown by the high T-value of 3.462 and a P-value of 0.000, indicating that AI-based decision help has a considerable impact on employability skills. With regard to Big Data Analytics (BDA), the path coefficients demonstrate that BDA has a positive influence on both Student Innovation (SI) and Employability Skills (ES), with path coefficients of 0.381 and 0.387, respectively. Low P-values (0.000 for both) and high T-values (5.932 and 5.830, respectively) indicate the strength of these associations.

Table 4. Path Coefficient

	Original Sample	T values	P Values
AIBDS -> SI	0.262	5.666	0.000
AIBDS -> ES	0.147	3.462	0.000
BDA -> SI	0.381	5.932	0.000
BDA -> ES	0.387	5.830	0.000

Note: AIBDS=AI Based Decision Support, BDA=Big Data Analytics, ES=Employability Skills, RA=Resource Availability, SI=Student Innovation, TA=Technology Acceptance.

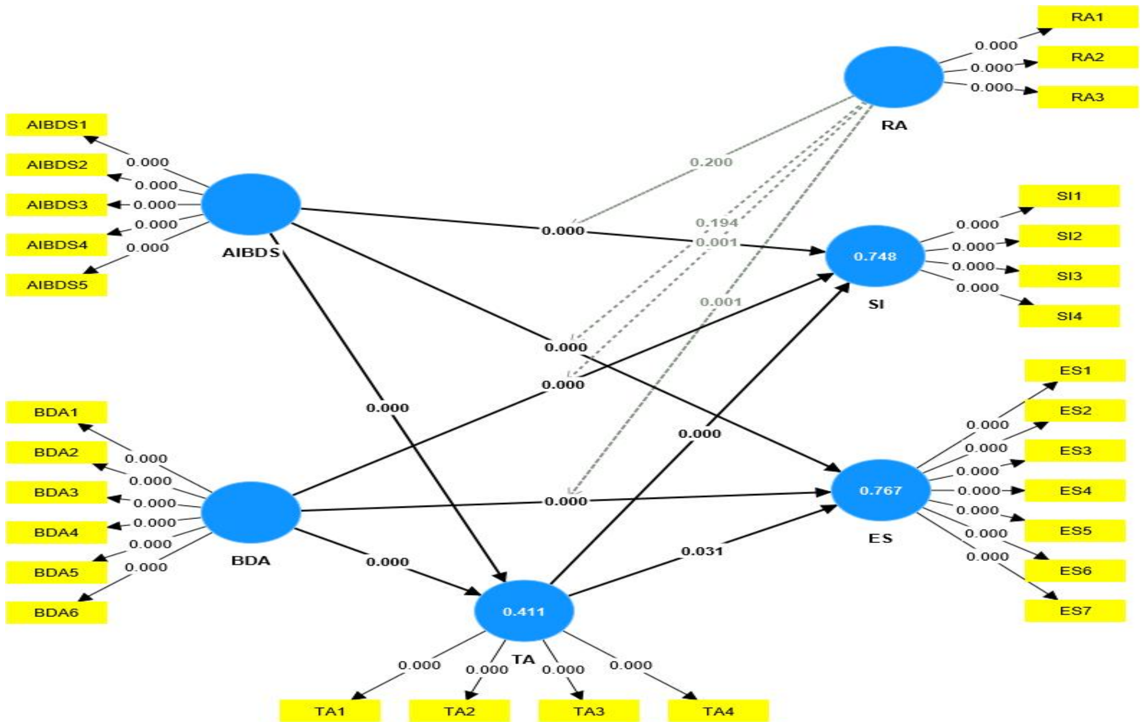

Figure 3. Structural Model

Table 5 summarizes the results of a mediation analysis that explores the complex interrelationships between variables and takes into account the mediating function of Technology Acceptance (TA). The path AIBDS -> TA -> SI demonstrates that AIBDS has a strong influence on Student Innovation via the mediator TA, with a path coefficient of 0.161. The statistical significance of this mediated association is confirmed by the high T-value of 4.987 and the unusually low P-value of 0.000, underscoring its significance in explaining the impact of AIBDS on SI. Furthermore, the path AIBDS -> TA -> ES indicates that AIBDS influences Employability Skills through TA, however, the path coefficient is lower at 0.026. However, it is statistically significant, showing that AIBDS indirectly influences ES through its impact on TA, as shown by a T-value of 1.744 and a P-value of 0.041. With the path coefficient of 0.106, the path BDA -> TA -> SI shows that Big Data Analytics significantly influences Student Innovation through the mediator TA. This association is extremely significant, with a T-value of 5.136 and a P-value of 0.000, indicating the function of BDA in influencing SI through TA. With a path coefficient of 0.017, BDA -> TA -> ES shows that BDA indirectly influences Employability Skills through TA. This mediated link is statistically significant, as evidenced by a T-value of 1.880 and a P-value of 0.030.

Table 5. Mediation Analysis

	Original Sample	T values	P Values
AIBDS -> TA -> SI	0.161	4.987	0.000
AIBDS -> TA -> ES	0.026	1.744	0.041
BDA -> TA -> SI	0.106	5.136	0.000
BDA -> TA -> ES	0.017	1.880	0.030

Note: AIBDS=AI Based Decision Support, BDA=Big Data Analytics, ES=Employability Skills, RA=Resource Availability, SI=Student Innovation, TA=Technology Acceptance.

Table 6 provides valuable insights from a moderation analysis, evaluating how the interaction between Resource Availability (RA) and AI-Based Decision Support (AIBDS) or Big Data Analytics (BDA) affects the dependent variables, Student Innovation (SI) and Employability Skills (ES). For the purpose of evaluating the importance of these interaction effects, the table includes coefficients, T-values, and P-values. In the cases of RA x AIBDS -> SI and RA x AIBDS -> ES, the coefficients indicate that RA and AIBDS have a favorable relationship on both Student Innovation and Employability Skills. These interactions are not statistically significant, as shown by the T-values of 0.841 and 0.862 and the P-values of 0.200 and 0.194, respectively. This implies that, when integrated with AI-based decision help, resource availability has no substantial impact on student innovation or employability skills in this setting. On the other hand, RA x BDA -> SI and RA x BDA -> ES show significant beneficial interaction effects between RA and Big Data Analytics on both Student Innovation and Employability Skills. The coefficients of 0.206 and 0.209 reveal these interactions, and the T-values of 3.123 and 3.139, coupled with low P-values of 0.001 for both, establish that they are statistically significant. This suggests that the availability of resources magnifies the impact of big data analytics on student innovation and employability skills, highlighting the importance of these factors separately in these domains.

Table 6. Moderation Analysis

	Original Sample	T values	P Values
RA x AIBDS -> SI	0.043	0.841	0.200
RA x AIBDS -> ES	0.038	0.862	0.194
RA x BDA -> SI	0.206	3.123	0.001
RA x BDA -> ES	0.209	3.139	0.001

Note: AIBDS=AI Based Decision Support, BDA=Big Data Analytics, ES=Employability Skills, RA=Resource Availability, SI=Student Innovation, TA=Technology Acceptance.

DISCUSSION

According to the results of Hypothesis 1, AI-based Decision Support Systems (DSS) significantly and favorably affect student innovation. The revolutionary potential of AI-based DSS in educational situations lends support to this view. These technologies provide individualized learning opportunities, on-demand coaching, and data-driven insights, adjusting instruction to the needs of each student (Shiang et al., 2022). AI-based DSS inspires creative thinking in students by presenting tailored problems and solutions. They allow for data-driven decision-making by providing insights on performance and potential development areas, enabling students to modify their strategies and experiment with original problem-solving techniques. The quick feedback loop enabled by AI-driven systems stimulates iterative processes, which are essential to innovation (Bertl et al., 2023). Furthermore, AI-based DSS frequently presents challenging tasks to students and facilitates collaborative problem-solving, fostering new solutions through teamwork. These systems curate a wide variety of instructional resources, exposing students to a wide range of perspectives and ideas that might drive creativity (Gołąb-Andrzejak, 2022). Another important element is learning efficiency, since AI-based DSS assists students in better managing their time, allowing them to devote more effort to new initiatives and undertakings.

According to the results of Hypothesis 2, AI-based Decision Support significantly and favorably affects Employability Skills. First off, these technologies offer students individualized instruction and data-driven insights, allowing them to improve their technical competence and adaptability — two essential traits for success in the modern labor market (Thomas, Senith, Alfred Kirubaraj, & Jino Ramson, 2022). As users interact with data-driven recommendations and make educated decisions, a talent that employers strongly appreciate, AI-based DSS also promotes data literacy. Furthermore, the problem-solving skills developed through interactive learning using AI-driven systems are directly transferable to professional settings (Thakar, Manisha, Mehta, Goel, & Verma, 2023). Furthermore, AI-based DSS promotes collaborative learning and teamwork, fostering communication and cooperation abilities that are highly valued by companies. These technologies enable collaborative projects that improve problem-solving and flexibility by connecting learners with similar interests and talents.

According to the results of Hypothesis 3, BDA's significant and positive impact on Student Innovation is grounded in its ability to unlock the power of data for educational improvement. BDA offers teachers and students priceless insights about learning styles, aptitudes, and deficiencies. BDA gives instructors the ability to customize their teaching strategies and foster an environment that is conducive to creative thinking by providing a data-driven understanding of students' development and performance (Peterson, 2018). This personalization generates a sense of ownership over one's education, which encourages creative exploration and problem-solving, both of which are essential components of innovation (Mccoll-Kennedy, Zaki, Lemon, Urmetzer, & Neely, 2019).

According to the results of Hypothesis 4, The notion that BDA positively impacts Employability Skills finds support in its ability to cultivate data literacy, analytical thinking, and adaptability among individuals. These talents are valued highly in the current job environment. BDA gives students the skills and information they need to successfully comprehend and apply data, a crucial ability in businesses that rely on it (Ojokoh et al., 2020). Additionally, individuals organically gain analytical thinking abilities as they participate in the BDA process, which is essential for problem-solving and decision-making in the professional world. BDA also promotes adaptation by exposing people to the continuously changing data and technological environment (Ezerins et al., 2022). Working with BDA systems encourages a readiness to adopt new technologies, a quality that employers strongly value in today's competitive labor market.

According to the results of Hypothesis 5, the mediation of Technological Acceptance in the relationship between AI-based Decision Support and Student Innovation finds support in the pivotal role of technology acceptance in education. Students and educators who quickly accept AI-based Decision Support Systems (DSS) are more likely to fully employ these tools, creating an environment favorable to innovation (Khan et al., 2023). Positive technology acceptance frequently leads to active involvement with AI-based DSS, which allows for individualized learning experiences, data-driven decision-making, and real-time feedback. These elements work together to create an environment that stimulates and supports students' inventive thinking (Zahlan, Ranjan, & Hayes, 2023). As a result, Technological Acceptance can be viewed as a facilitator of the positive influence of AI-based DSS on Student Innovation.

Results of Hypothesis 6 are rooted in the mediating role of Technological Acceptance, in the relationship between AI-based Decision Support and Employability Skills. People in the workforce are given the ability to actively interact with these systems when they quickly adopt and incorporate AI-based DSS into their professional tasks (Suha & Sanam, 2023). Their technological competence, data literacy, problem-solving skills, and adaptability are essential attributes of employability skills that are improved through this active participation. Technological Acceptance serves as a bridge, enabling AI-based DSS to more effectively affect the development of employable skills (Marescotti et al., 2022). It makes it easier for staff to use these tools, giving them access to data-driven insights and tailored advice that enhance their skill set.

According to the results of Hypothesis 7, the mediation of Technological Acceptance in the relationship between BDA and Student Innovation is substantiated by the fundamental role of technology acceptance in educational contexts. Students and teachers are more likely to use BDA tools efficiently and foster an innovative environment when they readily accept these tools (Aboelmaged & Mouakket, 2020). Positive attitudes toward technology stimulate active participation with BDA, opening the door to data-driven insights and individualized educational opportunities. This kind of involvement encourages students to think creatively as they use data to make informed decisions and conduct in-depth investigations (Shahbaz et al., 2019). As a result, Technological Acceptance serves as a bridge that allows BDA to fully realize its potential for enhancing Student Innovation.

The results of Hypothesis 8 are underpinned by the mediating role of Technological Acceptance, in the relationship between BDA and Employability Skills. These are essential elements of employability skills (Merry, Bettinger, Crosby, & Boston, 2023). Employees fully utilize BDA by using Technological Acceptance as a mediator, which improves their data literacy, analytical thinking, and flexibility. It makes it easier to use BDA systems, which in turn helps people build employable skills.

The discussion of Hypotheses 9 and 10 reveals that these hypotheses, which proposed that Resource Availability moderates the relationships between AI-based Decision Support and Student Innovation, as well as Employability Skills, were found to be statistically insignificant in our study. This implies that Resource Availability did not significantly alter the strength or direction of these relationships within the context of music colleges. Several factors may account for the lack of significance in these hypotheses. Firstly, the moderation effects of Resource Availability in educational settings can be intricate and multifaceted, potentially influenced by unexamined variables or complex interactions (Vellanki, Mond, Khan, & Nair, 2022). The specificity of the sample, consisting of music college students, could also be a contributing factor, as their unique characteristics and experiences might not align with broader educational contexts. Measurement considerations are another aspect to consider, as the perception and experience of resource availability may vary among students, impacting the results. Additionally, the cross-sectional design of the study may not capture potential changes in the moderating effect over time, warranting future longitudinal research.

The discussion of Hypotheses 11 and 12 Resource Availability moderates the relationship between BDA and Student Innovation. BDA can be widely used at educational institutions with plenty of resources to analyze huge datasets, customize instruction, and give students data-driven insights. With so many resources available, students can access and use BDA tools to encourage creative thinking (Bag, Wood, Xu, Dhamija, & Kayikci, 2020). Resource Availability moderates the relationship between BDA and Employability Skills. Organizations and educational institutions with a lot of money can put it towards a solid BDA infrastructure, training programs, and support mechanisms (LaForett & De Marco, 2020). Because individuals have access to the appropriate tools and training, this resource-rich environment promotes the development of employability skills such as data literacy, analytical thinking, and adaptability.

CONCLUSION

AI-based DSS and BDA emerge as powerful catalysts for change in education. They offer personalized learning experiences, fostering innovative thinking among students and enabling data-driven decision-making. These technologies provide a pathway to equip students with the vital Employability Skills essential for their future careers, including critical thinking, problem-solving, and adaptability. However, the journey towards harnessing the full potential of AI and BDA in education is not without its challenges. The study underscores the significance of Technological Acceptance, emphasizing the pivotal role of students and educators in embracing these technologies with enthusiasm. Equally important is the moderating role of Resource Availability, emphasizing the need for equitable access to resources, and ensuring that technology-driven benefits reach all students. AI-based DSS and BDA have the ability to alter education and prepare students for the changing workforce. This research affects educational institutions, policymakers, students, and employers. Teachers and institutions should use AI and BDA to improve education. Policymakers must encourage fair technology access and learning innovation. Students should adapt to modern technologies because they shape their academic and professional destinies.

LIMITATIONS AND FUTURE DIRECTIONS

Limitations

The generalizability of this study is one of its limitations. The findings may not be applicable to different educational levels, sectors, or cultural backgrounds because they are based on a particular setting or sample. Another weakness of this study is its cross-sectional design. While it allowed for the investigation of relationships between variables, it fell short of demonstrating causality. Longitudinal or experimental designs could be used in future studies to give more compelling evidence of the causal linkages between AI-based Decision Support, Big Data Analytics, Technological Acceptance, Resource Availability, creativity, and employability skills.

Another restriction is the reliance on self-reported data. Some data may be subject to biases or social desirability effects, such as people's opinions of innovation, technological acceptability, or employable abilities. Future research could use objective metrics or additional data sources to validate self-reported findings in order to address this constraint. Furthermore, the scope of this study's measurement of resource availability was broad; future research might delve further into specific resource kinds, such as financial, technical, or human resources, to acquire a more nuanced understanding of their varied influence on outcomes.

Future Directions

There are a number of intriguing directions this field of study could go in the future. The links that develop over time between AI-based Decision Support, Big Data Analytics, Technological Acceptance, Resource Availability, Innovation, and Employability Skills may be better understood by longitudinal studies. These studies would provide information on the long-term consequences of technology adoption in organizational and educational settings.

Experimental study designs provide yet another path for further investigation. Manipulation of variables such as Technological Acceptance through interventions may aid in more rigorously establishing causal links. Researchers can give more definitive proof of the impact of technology adoption by assessing the impact of these interventions on creativity and employability skills.

Contextual variables are still ripe for investigation. Future studies might examine how the correlations found in this study vary across a variety of cultural, industrial, and educational situations. Such research would provide insightful information about how resources and technology shape results in particular environments.

Future research could combine self-report data with objective assessments of innovation and employability skills to improve the reliability and validity of findings. Metrics such as project outcomes, job performance evaluations, or external assessments would provide for a more in-depth understanding of these dimensions.

ABOUT AUTHOR

Liu liu, studying for a Ph.D (doctor of fine arts) at International College of Krirk University in Bangkok, Thailand.

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