EDUCATIONAL BIG DATA MANAGEMENT FACTORS AFFECTING EFFECTIVENESS OF ART UNIVERSITIES IN SHENYANG CITY UNDER LIAONING PROVINCE

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Received: October 19, 2024; **Revised**: November 24, 2024; **Accepted**: December 28, 2024

Abstract

The objectives of this research were: (1) to study the component of educational big data management, the effectiveness of art universities, adoption technology skills, and teaching skills of art universities in Shenyang city under Liaoning Province; (2) to develop the model of educational big data management, adoption technology skills, and teaching skills factors affecting the effectiveness of art universities in Shenyang city under Liaoning Province, and (3) to decompose the effect of educational big data management, adoption technology skills and teaching skills on the effectiveness of art universities in Shenyang city under Liaoning Province. The population of this research was 1,037 teachers from 15 art universities in Shenyang city under Liaoning Province. The sample was 504 teachers, determined by the G*Power program (power of test .80), and using a stratified random sampling method. The data was analyzed by descriptive statistics, Confirmatory Factor Analysis, and Structural Equation Model.

The research found that: (1) Educational big data management components consisted of data collection, data storage and analysis, decision making, and impact on teaching. The components of effectiveness of art universities consisted of educational quality, student success, faculty excellence, research impact, and community engagement. The components of adoption technology skills consisted of technical proficiency, technology integration, training and support, and barriers to adoption. The components of teaching skills consisted of pedagogical competence, classroom management, communication skills, and assessment and feedback; (2) the model of factors affecting effectiveness of art universities fit well with empirical data (X^2/df=2.542, GFI=0.935, AGFI=0.912, NFI=0.926, IFI=0.954, CFI=0.953, TLI=0.944, RMSEA=0.055); and (3) educational big data management, adoption technology skills, and teaching skills had positive direct effect on effectiveness of art universities. Educational big data management had indirect effect on effectiveness of art universities via adoption technology skills and teaching skills, as the mediating effect. So, the effectiveness of art universities should be development on adoption technology skills and teaching skills together.

Keywords: Educational big data management, Effectiveness of art universities, Adoption technology skills, Teaching skills.

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Introduction

In the new century, a data and computing revolution, epitomized by "big data," had begun, exerting a profound impact on productivity across various sectors. "Big Data" technologies were transforming industries such as business, politics, and medicine, yet their application in education was still in its infancy. Amidst challenges to the scientific nature of education, the field was in urgent need of more scientific research methods, and the potential of big data was recognized as revolutionary in educational research (Xu Guoliang, 2001). China, aware of the strategic importance of big data, had seen its research methods widely applied in education by scholars, who believed it would lead to a new paradigm in educational research.

Liaoning Province, a key industrial and economic center, had experienced growth in higher education and an increasing demand for art education. Despite its achievements, the academic community had debated the scientific status of education and lacked unique research methods. Existing methods were largely categorized as either quantitative or qualitative (Liu Weiling, 2021). This paper aimed to provide theoretical guidance for the development of smart campuses in Shenyang's art universities by using multidisciplinary theories to study these issues and enrich the theoretical research on big data.

Research Question

1. What are the components of educational big data management, effectiveness of art universities, adoption technology skills and teaching skills factors in Shenyang under Liaoning Province?

2. What are the components of educational big data management, effectiveness of art universities, adoption technology skills and teaching skills factors in Shenyang under Liaoning Province?

3. How does the educational big data management, adoption technology skills and teaching skills effect affecting effectiveness of art universities in Shenyang under Liaoning Province?

Research Objectives

1. To study the component of educational big data management, effectiveness of art universities, adoption technology skills and teaching skills factors in art universities of Shenyang under Liaoning Province.

2. To develop the model of educational big data management, adoption technology skills and teaching skills factors affecting effectiveness of art universities of Shenyang under Liaoning Province.

3. To decompose the effect of educational big data management, adoption technology skills and teaching skills on the effectiveness of art universities of Shenyang under Liaoning Province.

Research Hypothesis

H1. Educational big data management factors had positive direct effect on the effectiveness of art universities.

H2. Adoption technology skills factors had positive direct effect on the effectiveness of art universities.

H3. Teaching skills factors had positive direct effect on the effectiveness of art universities.

H4. Educational big data management factors had positive direct effect on adoption technology skills.

H5. Educational big data management factors had positive direct effect on teaching skills.

H6. Educational big data management factors had indirect effect on effectiveness of the art universities via adoption technology skills.

H7. Educational big data management factors had indirect effect on effectiveness of the art universities via teaching skills.

Research Methodology

This section outlines the research methodology as follows;

1. Population and sample group

The population of this research was 1037 from 15 art universities located in Shenyang under Liaoning Province. The sample was 504 teachers which determined by G*Power program at power of test .80, and stratified random sampling method.

2. Scope of Study

Developing a conceptual framework entail establishing the foundational ideas, theories, and principles that guide this research, as the conceptual framework below.

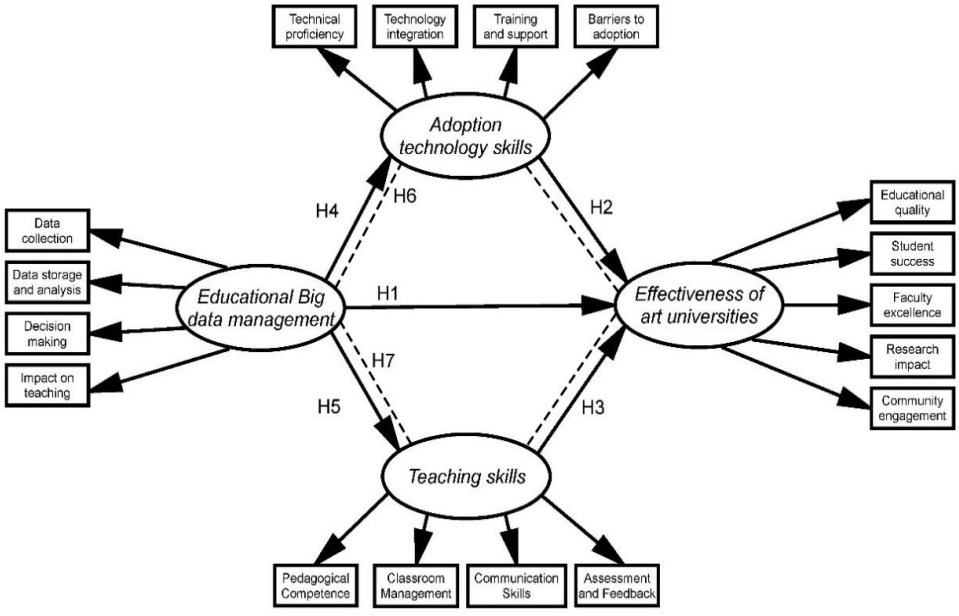


Figure 1 Conceptual Framework

3. Research tool

A structured survey a five-point scale questionnaire is used to gather demographic information and assess respondents' perceptions of four factors, including Educational big data management, Effectiveness of art universities, Adoption technology skills, and Teaching skills. To ensure the validity of the questionnaire, each question was assessed for the Index of Objective Congruence (IOC), and all of these questions exceeded between 0.60-1.00. Additionally, the reliability of the questionnaire was confirmed through Cronbach's alpha coefficients ranging between 0.86-0.89 for each variable. These results were good reliability, (Cortina, 1993) on validity and reliability.

4. Data analysis

The data analysis on descriptive statistics with mean, standard deviation, skewness, and Kurtosis (Hair et al, 2007) and test the hypothesis of this study with confirmation factors analysis (CFA) and Structural equation modeling (SEM) on the model fit indicators, model measurement quality and the effect of factor by statistical package software. The criterion

Indicated for the model CFA is acceptable when fitting with empirical data. (Hu & Bentler, 1998) in Table 1.

Table 1. Show the criterion on indicators in CFA model.

Indicator	Terrible	Acceptable	Excellent
Chi-square/df	>5	>3	>1
CFI	< .90	<0.95	>0.95
GFI	< .90	<0.95	>0.95
NFI	< .90	<0.95	>0.95
RESEA	> .08	> 0.06	<0.06

Results

The results of the research, present four topics, including Descriptive data analysis, Confirmation factor analysis model, Hypothesis model, and Hypothesis testing as follows:

1. Descriptive data analysis

The research results on the descriptive analysis, shown in Table 2

Table 2 Descriptive analysis

Latent variables	Component	$\bar{X}$	S.D.	Level	%CV	Skewness		Kurtosis	
						Skewness	SE	Kurtosis	SE
EAU	EAU1	3.76	1.00	high	0.27	-1.09	0.10	0.21	0.21
	EAU2	3.78	1.01	high	0.27	-1.11	0.10	0.14	0.21
	EAU3	3.88	0.91	high	0.23	-1.41	0.10	0.86	0.21
	EAU4	3.88	0.91	high	0.24	-1.30	0.10	0.73	0.21
	EAU5	3.73	0.98	high	0.26	-1.10	0.10	-0.10	0.21
ATS	ATS1	3.90	0.81	high	0.21	-1.39	0.10	1.64	0.21
	ATS2	3.85	0.92	high	0.24	-1.23	0.10	0.53	0.21
	ATS3	3.73	1.01	high	0.27	-1.14	0.10	0.05	0.21
	ATS4	3.71	1.02	high	0.28	-1.08	0.10	0.05	0.21
EBDM	EBDM1	3.97	0.74	high	0.19	-1.65	0.10	2.51	0.21
	EBDM2	3.79	0.95	high	0.25	-1.16	0.10	0.08	0.21
	EBDM3	3.67	0.99	high	0.27	-0.88	0.10	-0.47	0.21
	EBDM4	3.89	0.87	high	0.23	-1.51	0.10	1.28	0.21
TS	TS1	3.94	0.81	high	0.21	-1.62	0.10	1.84	0.21
	TS2	3.68	0.98	high	0.27	-0.94	0.10	-0.44	0.21
	TS3	3.63	0.99	high	0.27	-0.75	0.10	-0.85	0.21
	TS4	3.71	0.98	high	0.26	-0.99	0.10	-0.26	0.21

From Table 2, descriptive statistics for all observed variables used in the study, were EAU, ATS, EBDM, and TS. The overall was a high level. These statistics are computed based on collected sample data, providing insights into the fundamental characteristics and distributions of these variables as normal curves with a Skewness value of less than 3 and a Kurtosis value of less than 8 (Curran, West, and Finch, 1997). The correlation between latent variables in Table 3.

Table 3 show the correlation between latent variables.

	EAU	ATS	EBDM	TS
EAU	1			
ATS	.35**	1		
EBDM	.42**	.29**	1	
TS	.47**	.32**	.35**	1

**P < 0.01

The correlation analysis results in Table 3: The Pearson correlation had values between .29 to .47 with significance ($p < .01$). They were suitable for CFA and SEM model analysis. Show the CFA model as Figure 2.

2. Measurement model

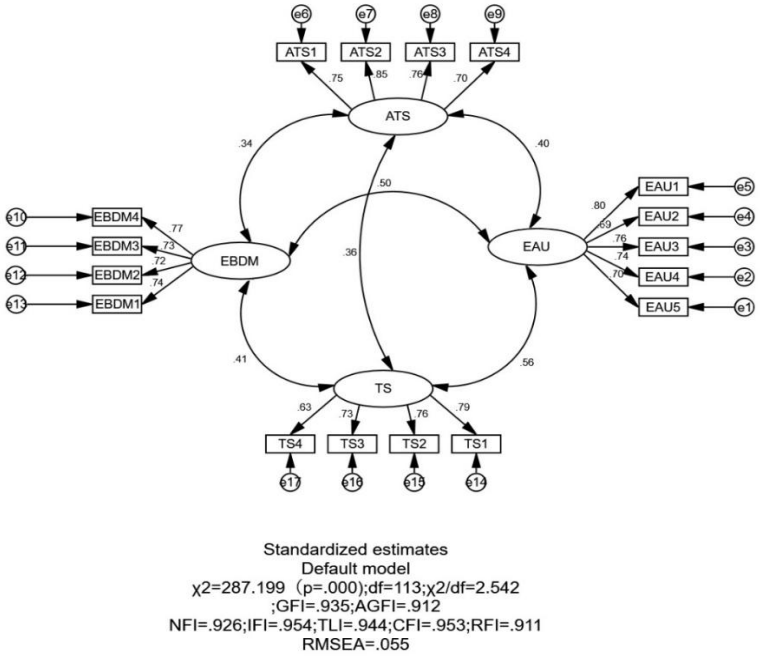


Figure 2 Measurement Model

The following pivotal statistical data provided a comprehensive assessment of the model's fit: Chi-square=287.199, Df=113, Chi/Df=2.542, GFI=0.935, AGFI=0.912, NFI=0.926, IFI=0.954, TLI=0.944, CFI=0.953, RFI=0.911, RMSEA=0.055. These statistics supported the notion that the model exhibited a good degree of fit with the observed data. The specific results are shown in Table 4.

Table 4. The results of statistics and indicators to evaluate the model fit.

Reference index	Standard values	Estimate	Interpretation
X^2/df	<3	2.54	Excellent
GFI	>0.8	0.93	Excellent
AGFI	>0.8	0.91	Excellent
NFI	>0.9	0.92	Excellent
IFI	>0.9	0.95	Excellent
CFI	>0.9	0.95	Excellent
TLI	>0.9	0.94	Excellent
RMSEA	<0.08	0.05	Excellent

From Table 4, shown that the model CFA had fit well with the empirical data which all indicators were excellent level. The researcher was analysis on the model quality by composite reliability (CR), Convergent validity (AVE), and discriminant validity (Fornall and Larcker, 1981) shown in Table 5.

Table 5 Composite reliability (CR), Convergent validity (AVE), and discriminant validity

	CR	AVE	EAU	ATS	EBDM	TS
EAU	0.85	0.55	**0.73**			
ATS	0.85	0.59	0.35	**0.76**		
EBDM	0.82	0.54	0.42	0.29	**0.74**	
TS	0.82	0.53	0.47	0.32	0.35	**0.73**

In order to identifying the latent variable reliability, the Composite reliability (CR) of 4 factors raged from 0.821 to 0.857 which were over 0.7., and to identifying the convergent validity, the AVE value was required to be greater than 0.5, indicating that each variable facet had good convergent validity, to identify the discriminant validity by the method of Forell & Larcker (198l), the square root of AVE of latent variables must be more than its shared variance toother latent variables.

3. Structural Equation Model

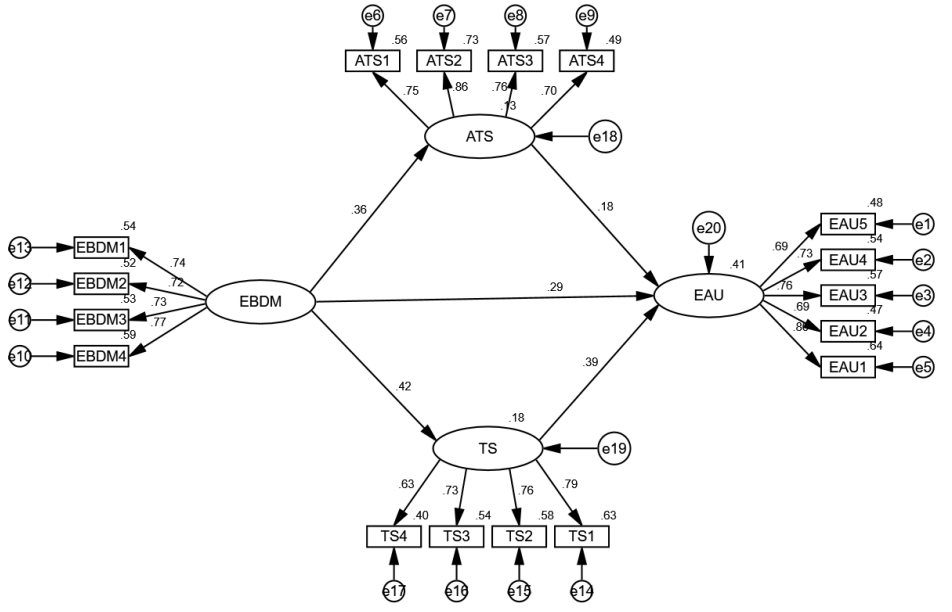


Figure 3. Structural equation model in standardized

A The assessment of the structural model's fit revealed the following goodness of-fit statistics: the X^2/df value was 2.709, which was less than the ideal standard of 3. The values for the goodness-of-fit indices were as follows: GFI = 0.931, AGFI = 0.908, NFI = 0.920, IFI = 0.948, CFI = 0.948, and TLI = 0.938. The RMSEA test result was 0.058, which was below the standard level of 0.08. All goodness-of-fit indices of the structural equation model established in this study met or exceeded the general standard values, indicating that the structural equation model was effectively established and had a good fit with the empirical data, and could be deduced the effect of the hypothesis as follow.

Table 6 Testing result for direct effect hypothesis

Relationship	Unstandardized	Standardized	S.E.	C.R.	P	Hypothesis
EAU<---EBDM	0.290	0.289	0.057	5.104	***	H1
EAU<---ATS	0.198	0.178	0.054	3.694	***	H2
EAU<---TS	0.407	0.385	0.058	6.993	***	H3
ATS<---EBDM	0.322	0.356	0.049	6.603	***	H4
TS<---EBDM	0.398	0.419	0.052	7.652	***	H5

***P＜0.001

The analysis of Table 6 shown that all the direct hypotheses (H1 to H5) exhibited statistically significant effects, as indicated by their C.R. values and significance indicators. The effect among the latent variables, could be shown on the indirect effect at the Table 7.

Table 7 Decomposition of indirect effect hypothesis

Relationship	Estimate	95%CI		P	Hypothesis
		Lower	Upper		
EAU <---ATS<---EBDM	0.063	0.022	0.139	0.001	H6
EAU<---TS<---EBDM	0.162	0.087	0.280	0.000	H7

Table 7 presented the results of the impact decomposition for indirect effects, as determined through a multi-step path analysis. These indirect paths signified the channels through which influence was channeled via intermediate latent variables. The subsequent analysis explored the standardized effects of these indirect paths, along with their associated 95% confidence intervals.

The findings from these decomposed effect analyses offered critical insights into the mediating functions of various intermediate variables across distinct hypotheses.

Conclusion

1. The components of educational big data management were data collection, data storage and analysis, decision-making, and impact on teaching. The components of adoption technology skills were technical proficiency, technology integration, training and support, and barriers to adoption. The components of the effectiveness of art universities were educational quality, student success, faculty excellence, research impact, and community engagement. The components of teaching skills were pedagogical competence, classroom management, communication skills, and assessment and feedback.

2. The model of educational big data management, adoption technology skills, and teaching skills factors affecting the effectiveness of art universities of Shenyang under Liaoning Province fit well with empirical data (X^2/df=2.542, GFI=0.935, AGFI=0.912, NFI=0.926, IFI=0.954, CFI=0.953, TLI=0.944, RMSEA=0.055).

Educational big data management, adoption technology skills, and teaching skills were the factors affecting the effectiveness of art universities. Educational big data management was the factor affecting adoption technology skills and teaching skills. Adoption technology skills was the factor affecting teaching skills. Adoption technology skills and teaching skills were the indirect factors affecting the relationship between educational big data management and the effectiveness of art universities.

3) Educational big data management, adoption technology skills, and teaching skills had positive direct effect on effectiveness of art universities. The educational big data management had indirect effect on effectiveness of art universities via adoption technology skills and teaching skills, as mediation effect.

Discussion

In this research was found that:

Hypothesis 1 suggested that educational big data management positively impacts the effectiveness of art universities. Empirical research confirmed this, with educational big data management showing a significant positive effect on effectiveness (path coefficients: unstandardized 0.292, standardized 0.290, $p<0.001$). This aligns with Liu Juan's (2017) findings on the development mechanism of teaching ability in local college teachers. Hypothesis 2 proposed that technology adoption skills positively affect the effectiveness of art universities. Empirical research revealed a significant positive effect, with path coefficients of 0.185 (unstandardized) and 0.164 (standardized), $p<0.001$. This supports Macfadyen (2014) who found that technology adoption skills directly enhance university effectiveness. Hypothesis 3 posited that teaching skills have a positive direct effect on the effectiveness of art universities. Empirical research confirmed this, with path coefficients of 0.412 (unstandardized) and 0.384 (standardized), $p<0.001$, indicating a significant positive impact. This aligns with Storey (2017), who found a positive correlation between teaching skills and effectiveness. Hypothesis 4 suggested that educational big data management positively influences technology adoption skills. Empirical research confirmed a significant positive effect, with path coefficients of 0.304 (unstandardized) and 0.340 (standardized), $p<0.001$. This aligns with Stojanov (2023), who found that higher levels of educational big data management correlate with more positive application and promotion of new teaching technologies in higher education. Hypothesis 5 proposed that educational big data management positively impacts teaching skills. Empirical research revealed a significant positive effect, with path coefficients of 0.302 (unstandardized) and 0.321 (standardized), $p<0.001$. This supports Lu Jing's (2013) findings that educational big data management commitment positively affects teaching skills.

Furthermore, Hypothesis 6 and Hypothesis 7 examined the indirect effects of technology adoption skills and teaching skills on the relationship between educational big data management and the effectiveness of art universities. Empirical research indicated that technology adoption skills mediated this relationship with a value of 0.056, and teaching skills with a value of 0.123, both with confidence intervals excluding zero. This demonstrated that both technology adoption skills and teaching skills played mediating roles in the impact of educational big data management on the effectiveness of art universities.

Recommendations

1. From the perspective of Educational Big Data Management

In the digital age, effective educational big data management and application are pivotal. This involves comprehensive processes like data collection, processing, analysis, and visualization, contributing to personalized talent development, teaching enhancement, evaluation, and resource sharing. The digital transformation of education, a key part of the national digital education strategy, encompasses fostering digital awareness, capabilities, smart education ecosystems, and governance systems. This transformation requires comprehensive digitalization across education sectors, promoting overall sector advancement. To maximize the role of educational big data in university management, it's essential to raise awareness, establish hierarchical data centers, streamline management systems, and implement supportive policies like guidelines, regulations, and research institutions. These measures lay a robust foundation for future education sector development.

2) From the perspective of Adoption Technology Skills

In higher education, the integration of technology and skills is crucial for modernization and teaching quality. Universities should prioritize teacher technical competency development through systematic training, interdisciplinary projects, and the

establishment of technical practice communities. Adequate technical support and resources, along with innovation project funds, should be provided to encourage teachers to engage in innovative teaching practices. A scientific evaluation mechanism should be established to regularly assess and certify teacher technical skills, ensuring continuous improvement and professional development. These strategies promote the deep integration of educational technology, enhancing overall education quality and effectiveness.

3) From the perspective of Teaching Skills

In higher education, refining teaching skills is paramount. Universities should prioritize faculty pedagogical competency through regular training, workshops, and mentorship programs. Collaborative platforms and resource-sharing initiatives foster a culture of professional dialogue and innovation. Self-reflection and evaluation help teachers identify strengths and areas for improvement, while student engagement and feedback enhance instructional approaches. Leveraging educational technology, such as online platforms and virtual labs, can make teaching more dynamic and engaging. These comprehensive strategies optimize instructional methodologies, elevating faculty teaching skills and overall educational quality.

4) From the perspective of Effectiveness of Art Universities

To enhance pedagogical efficacy in art universities, strategic interventions were essential. Emphasizing experiential learning through studios, exhibitions, and venues fostered students' creativity. Tailored education respected students' unique interests and offered diverse courses and teaching approaches. Attracting and cultivating high-quality art educators, providing professional growth opportunities, and collaborating with art industries and cultural organizations reinforced the industry-education-research alliance. International collaborations and exchanges brought global resources, expanding students' horizons and enhancing the university's international reputation. These holistic strategies significantly improved education quality, nurtured innovative artists, and elevated the institutions' international standing.

Recommendations for Future Research:

For the field of educational big data management and its implications for the effectiveness of art universities in Shenyang, Liaoning Province, the direction of future research should have been guided by the following considerations:

Firstly, future inquiries should have delved into the exploration and broadening of the sources and types of educational big data. This encompasses, but is not limited to, student demographics, learning behaviors, curriculum design, and teaching evaluations. A more profound understanding of the determinants of effectiveness in art universities could have been attained through the analysis of a more extensive array of data. Moreover, the utilization of diverse research methodologies, such as case studies, comparative analyses, and experimental research, could have facilitated a more sophisticated comprehension of the relationship between educational big data management and the effectiveness of art universities.

Secondly, future research should have been attentive to the evolutionary trends in policies and management practices. As educational policies and management approaches are subject to change, these shifts could have substantially influenced the management of educational big data and, consequently, the effectiveness of art universities. By monitoring and analyzing these developments, researchers could have provided insights into how art universities might have adapted their data management strategies to accommodate new policies and practices.

Lastly, there was an imperative for interdisciplinary collaboration and exchange. The intricate nature of educational big data management and its relevance to the effectiveness of art universities necessitated input from a variety of disciplines, including computer science, statistics, and psychology, among others. By encouraging such interdisciplinary collaboration,

future research could have capitalized on a wider spectrum of theories and technical expertise, thereby enriching the depth and breadth of the scholarly inquiry. Additionally, addressing the security and privacy concerns associated with educational big data was of paramount importance. Future research should have investigated strategies for effectively harnessing educational big data while ensuring the protection of student and faculty privacy.

In summation, future research endeavors should have aimed to broaden the scope and depth of data analysis, employ a variety of research methodologies, and remain attuned to shifts in policies and management practices. By fostering interdisciplinary collaboration and addressing security and privacy concerns, researchers could have furnished art universities with actionable insights to enhance their effectiveness in the management of educational big data.

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