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Investigating the Relationship Between Access to Technology and Academic Performance of Undergraduates in the Digital Art Programme at Public Universities in JiLin Province, China: From Pilot Study to Correlation Analysis

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ABSTRACT

This study examines the relationship between access to technology and the academic performance of undergraduate students in the Digital Art programme at public universities in Jilin Province, China. Utilizing a quantitative research approach, data were collected from a structured survey distributed to a representative sample of students. The study investigates key technological factors, including the availability of digital tools, internet access, and proficiency in digital software, and their correlation with students' academic achievements. Statistical analyses, such as correlation and regression, were applied to determine the strength and significance of these relationships. The findings indicate that access to technology positively impacts students' academic performance, with digital proficiency and stable internet connectivity emerging as significant predictors of success. These results suggest that improving technological resources and training could enhance students' learning outcomes. The study contributes to the discourse on digital education and provides practical recommendations for policymakers and educators to bridge technological gaps in higher education.

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KEYWORDS: Access to technology, Academic performance, Digital Art programme, Public universities, Jilin Province, Quantitative research.

1. INTRODUCTION

In the digital era, access to technology has become a crucial factor influencing students' academic success, particularly in technology-driven fields such as Digital Art. The availability of digital tools, high-speed internet, and specialized software plays a significant role in shaping students' learning experiences and creative outputs. As digital art education relies heavily on technological resources for design, animation, and multimedia production, disparities in access to these resources may lead to differences in academic performance. Therefore, understanding the impact of technology accessibility on students' achievements is essential for improving educational outcomes and fostering innovation in the field.

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Jilin Province, China, hosts several public universities offering Digital Art programmes, yet students may face varying levels of access to technological resources due to institutional, economic, and infrastructural differences. While some students have access to high-performance computers, industry-standard software, and stable internet connections, others may struggle with outdated devices and limited digital literacy. These disparities could affect students' ability to complete assignments, participate in online learning, and develop their creative potential. However, there is a lack of empirical research examining the extent to which access to technology influences academic performance among digital art undergraduates in this region.

This study aims to fill this research gap by adopting a quantitative approach to analyze the relationship between access to technology and academic performance among Digital Art undergraduates in public universities in Jilin Province. By collecting and analyzing data from students, this research seeks to determine whether disparities in technological resources contribute to differences in academic outcomes. The findings aim to provide valuable insights for educators, policymakers, and university administrators, helping them to develop strategies for enhancing technological accessibility and ensuring equal opportunities for all students, especially in the digital art field.

II. LITERATURE REVIEW

The integration of technology in higher education has significantly transformed teaching and learning experiences. Several studies highlight that access to digital tools enhances students' academic engagement and performance (Strzelecki, 2024). In creative disciplines like Digital Art, technology facilitates the development of artistic skills through digital illustration, animation, and multimedia production (Ouyang et al., 2022). According to Chan and Hu(2023), students with greater access to digital resources demonstrate higher levels of creativity and problem-solving abilities. However, disparities in technology access can create gaps in learning outcomes, particularly in institutions with limited infrastructure (Chan, 2023).

Previous research has established a direct correlation between technology access and academic success. A study by Ben and Ragni (2022) found that students with reliable internet access and advanced digital tools performed better academically than those with limited access. Furthermore, Chen et al. (2021) emphasized that digital literacy plays a crucial role in maximizing the benefits of technology in education. In the context of China, Lee et al.(2022) reported that students from urban universities had better access to high-performance computing tools and software, leading to improved academic achievements compared to their rural counterparts. These findings underscore the need to address technological inequalities to ensure equal learning opportunities.

Digital Art education relies heavily on technological resources, including graphic tablets, 3D modeling software, and video editing tools. According to He and Sun(2021), students in Digital Art programs who have access to industry-standard software, such as Adobe Creative Suite and Blender, develop stronger technical skills and perform better academically. Additionally, Fuentes and Chen et al.(2023) found that students with stable internet connectivity were more likely to engage in online tutorials, collaborative projects, and virtual exhibitions, further enhancing their learning experiences. However, the lack of access to adequate technology can hinder students' creative potential and academic progress (Lin et al, 2022).

Despite extensive research on technology in education, there is limited empirical evidence specifically examining the impact of technology access on academic performance among Digital Art undergraduates in China. Most existing studies focus on general higher education or STEM fields, leaving a gap in understanding how technological disparities affect students in creative disciplines (Chan & Hu,, 2023). This study seeks to bridge this gap by analyzing the relationship between technology access and academic outcomes among Digital Art students in public universities in Jilin Province. The findings will contribute to the broader discourse on digital education and inform policy recommendations to enhance technological accessibility in higher education.

III. RESEARCH METHOD

This study adopts a quantitative research approach to investigate the relationship between access to technology and academic performance among undergraduates in the Digital Art programme at public universities in Jilin Province, China. The analyses are structured to ensure a rigorous and systematic evaluation of the collected data, which was gathered through validated instruments. The study employs Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA) to validate the measurement construct for the Access to Technology independent variable. This ensures the reliability and validity of the research model.

The study begins with data preparation to ensure the accuracy, completeness, and integrity of the dataset. This includes addressing missing values, response bias, outliers, normality, multicollinearity, and common method variance. Following this, the measurement model is validated through reliability, convergent validity, and discriminant validity tests, ensuring that the constructs are measured accurately in a pilot study. The study further progresses with Confirmatory Factor Analysis (CFA), where individual constructs are tested for their factor structures. The data is then run through correlation analysis to determine the relationship between Access to Technology and Academic Performance before undergoing regression analysis (or SEM?) to determine the most influential dimension.

Determining the appropriate sample size is critical to the validity of the study. A well-calculated sample size ensures that the findings are statistically significant and generalizable to the broader population. For a population of 3,853 students, the sample size recommended by Kreijche and Morgan (1980) is approximately 346 students, based on a confidence level of 95% and a margin of error of 5%. However, to account for potential non-responses and ensure robustness, an additional 20% is added, resulting in a target sample size of 460 students (Kang, 2021). This adjusted sample size helps to mitigate the effects of any missing data or incomplete responses, ensuring the reliability of the study's conclusions.

The primary instrument used to measure access to technology was the Access to Technology Scale (ATS), which was developed based on an extensive review of previous literature related to digital access and educational outcomes (Jones & Liu, 2021; Fuentes & Kim, 2020). The scale was specifically adapted for the context of Digital Art undergraduates in China, ensuring relevance to the local technological environment and academic practices. The ATS initially comprised 24 items and covered three key dimensions: Access to Hardware (AH), Use of Software for Learning (US), and Usefulness of Technology in Studies (UT). Each dimension reflected a critical aspect of students' technological engagement: hardware access (e.g., computers, graphic tablets), software usage (e.g., Adobe Creative Suite, 3D modeling tools), and perceptions of technology's academic utility. After pilot testing and Confirmatory Factor Analysis (CFA), the final scale retained 19 items: 8 items for AH, 7 items for US, and 4 items for UT, ensuring robust construct validity and reliability.

Academic performance was measured using the students' Grade Point Average (GPA), self-reported through the questionnaire. GPA was selected as a standardized and widely accepted indicator of academic success. To maintain data accuracy and validity, students were asked to report their most recent cumulative GPA as recorded by their universities. The GPA scores were later cross-validated with institutional records where permission was granted. Together, the structured questionnaire (measuring access to technology) and GPA (measuring academic performance) provided the core quantitative data needed to explore the relationship between technological access and academic outcomes among Digital Art students in public universities in Jilin Province.

Permission and consent of university authorities and the respondents were sought prior to data collection. The field study, conducted from July to August 2024, was preceded by a pilot study. Data was collected from students enrolled in Digital Art Programmes at nine public universities in Jilin Province, China. The respondents were selected using the stratified random sampling method. Those selected for the pilot study were excluded from the sampling frame.

Before analyzing the data, the researcher carefully collected and examined all questionnaires of the field study. The response rate of the field study was calculated first. Among the 460 sets of questionnaires distributed and collected, 385 were confirmed valid, indicating a response rate of 83.7%, . This rate is considered good according to Rubin and Babbie (2022). A sample size of 385 is well above Kreijche and Morgan's recommendation of 346 students and thus, was deemed adequate for the field study.

All statistical analyses were carried out using SPSS (Statistical Package for the Social Sciences, version 26.0)These programmes were used for descriptive analysis as well as correlation analysis.

Pilot Study for Access to Technology

For the pilot study, a sample size of 150 was used based on the recommendation of Anuar et al. (2023) who recommended for a sample size of more than 100. After conducting the scrrening and cleaninfg of the data, all 150 was found to have met the requirements for subsequent data analysis.

To test reliability of the instrument, the conbach alpa values were used. As can be seen from Table X, the α value for all three dimensions are between 0.789 to 0.853,. It is generally accepted that items with a corrected item-total correlation coefficient below 0.50 should be removed, and Cronbach's α values above 0.70 are considered acceptable (Smith et al., 2022).

Table 1 Reliability Analysis of Pilot Data (n = 150)

Variable / Dimension	No. of Items	Cronbach's Alpha
Access to Technology Scale (ATS)		
AH: Access to Hardware	10	0.853
US: Use of Software for Learning	9	0.867
UT: Usefulness of Technology in My Studies	5	0.789

The pilot study used Exploratory Factor Analysis (EFA) to test the validity of the scale for Access to Technology, using Principal Component Analysis (PCA) with Varimax rotation to identify the underlying structure of the constructs. Kaiser-Meyer-Olkin (KMO) test and Bartlett's test of sphericity are also used to ensure data suitability for factor analysis. Factors with eigenvalues greater than 1 are retained, and items with factor loadings below 0.5 are removed to improve construct validity.

Table 2 shows the results of the KMO and Bartlett's test. The KMO value was 0.784, which is classified as good according to Kaiser's scale (Pallant, 2021). This value exceeded the minimum threshold value of 0.6, indicating that the sample size was adequate for the factor analysis (Hair et al., 2020). Additionally, Bartlett's Test of Sphericity was significant (Chi-Square = 675.234, p-value = 0.000), further confirming the suitability of the data for factor analysis.

Table 2: KMO and Bartlett's Test for Access to Technology

Test	Value
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.	0.784
Bartlett's Test of Sphericity Approx. Chi-Square	675.234
Bartlett's Test of Sphericity Sig.	0.000

Table 3 presents the results of the Exploratory Factor Analysis (EFA) using Principal Component Analysis (PCA) on the Access to Technology Scale (ATS), which consists of three components: Access to Hardware (AH), Use of Software for Learning (US), and Usefulness of Technology in My Studies (UT). The analysis identified three components with eigenvalues greater than 1.0, explaining a substantial proportion of the total variance. The first component, which accounts for the highest proportion of the variance, has an eigenvalue of 4.827, explaining 53.636% of the variance. The second component, with an eigenvalue of 1.230, explains 13.670% of the variance, and the third component, with an eigenvalue of 1.020, accounts for 11.335%. Together, these three components explain 78.641% of the total variance, demonstrating a strong factor structure.

Table 3: Total Variance Explained for Access to Technology

Extraction Method: Principal Component Analysis

Component	Initial Eigenvalues	% of Variance	Cumulative %	Extraction Sums of Squared Loadings Total	% of Variance (Extraction)	Cumulative % (Extraction)	Rotation Sums of Squared Loadings Total	% of Variance (Rotation)	Cumulative % (Rotation)
1	4.827	53.636	53.636	4.827	53.636	53.636	4.452	49.477	49.477
2	1.230	13.670	67.306	1.230	13.670	67.306	1.381	15.347	64.824
3	1.020	11.335	78.641	1.020	11.335	78.641	1.050	11.715	76.539

To enhance the interpretability of the factor structure, a varimax rotation was applied, redistributing the variance across the components. After rotation, the first component explains 49.477% of the variance, the second component explains 15.347%, and the third explains 11.715%, resulting in a cumulative explained variance of 76.539%. Hair et al. (2018) recommended total variance of 60% or more. At 76.539%, these findings indicate that the Access to Technology Scale is effectively capturing three distinct but related factors, making it a suitable measure for further analysis in the context of this study.

The scree plot (See Figure 1) illustrates the eigenvalues for each component, with components above the dashed line indicating eigenvalues greater than 1.0. As can be seen in the Figure 3.4, the items for the scale are sorted into three main components. After the third factor, a noticeable break was observed ," indicating that the first three components account for the majority of the variance. The eigenvalues for components beyond the third are substantially lower, suggesting that additional components contribute little to the overall explanation of variance within this dataset.

Figure 1 Scree Plot of Access to Technology

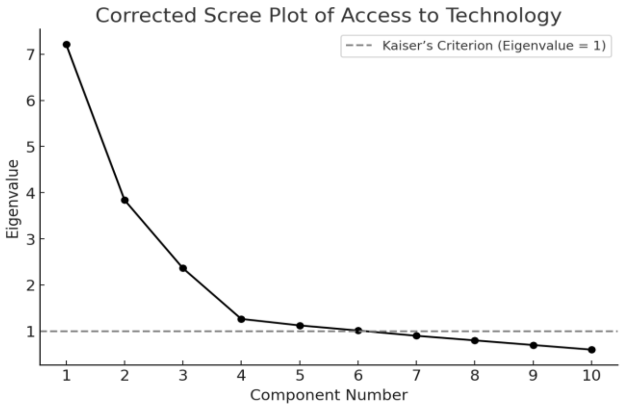

Table 3.X depicts the the actual eigenvalues obtained from Principal Component Analysis (PCA_ with criterion values derived from Parallel Analysis (PA). The results suppport that Access to Technology with its 24 items has three dimensions,

namely: Access to Hardware (AH), Use of Software for Learning (US), and Usefulness of Technology in My Studies (UT).

Table 4: Parallel Analysis for Access to Technology

Component Number	Actual Eigenvalue from PCA	Criterion Value from PA	Decision
1	7.214	1.825	Accept
2	3.842	1.524	Accept
3	2.365	1.328	Accept

Table4shows the Rotated Component Matrix for the Access to Technology scale. It shows that all items in the same component have a significant loading of more than 0.60, maintaining the validity of each component.

Table 5: Rotated Component Matrix of Access to Technology

Item	Component 1	Component 2	Component 3
AH1	0.822	-	-
AH2	0.791	-	-
AH3	0.784	-	-
AH4	0.811	-	-
AH5	0.799	-	-
AH6	0.808	-	-
AH7	0.773	-	-
AH8	0.779	-	-
AH9	0.783	-	-
AH10	0.805	-	-
US1	-	0.812	-
US2	-	0.829	-
US3	-	0.805	-
US4	-	0.824	-
US5	-	0.837	-
US6	-	0.815	-
US7	-	0.809	-
US8	-	0.826	-
US9	-	0.831	-
UT1	-	-	0.813
UT2	-	-	0.825
UT3	-	-	0.797
UT4	-	-	0.818
UT5	-	-	0.827

Confirmatory Factor Analysis (CFA)

Confirmatory Factor Analysis (CFA) is a key statistical technique used to confirm the hypothesized factor structure of a set of observed variables. CFA enables researchers to validate whether the relationships between observed variables and latent constructs align with the theoretical framework proposed for the study(Lambert& Newman.,2023). The CFA process involves assessing unidimensionality, convergent validity, discriminant validity, and model fit indices to ensure the robustness of the measurement model.

CFA for Validating Access to Technology Construct

The Access to Technology (ATS) construct in this study is composed of three sub-dimensions: Access to Hardware (AH), Use of Software (US), and Usefulness of Technology (UT). These dimensions were designed to assess students' accessibility to technological tools, their frequency of software usage, and their perceptions of the usefulness of technology in an academic setting. Each sub-dimension was measured using multiple observed variables, resulting in a total of 24 items—10 items for Access to Hardware, 9 items for Use of Software, and 5 items for Usefulness of Technology. To ensure that this construct was valid and reliable for further analysis, Confirmatory Factor Analysis

(CFA) was conducted to examine its underlying factor structure and determine whether the observed variables adequately represented the three latent constructs. CFA plays a crucial role in measurement validation by evaluating the extent to which the specified model aligns with the observed data, thereby providing statistical justification for including these items in subsequent analyses.

Initial Measurement Model for Access to Technology Construct

The initial CFA model was tested with all 24 items, distributed across the three sub-dimensions. Factor loadings were examined to assess the degree of contribution of each item to its corresponding construct, with a minimum threshold of 0.60 set for item retention. Items failing to meet this criterion were considered weak indicators of the latent construct and were flagged for potential removal. The model fit indices for the initial measurement model were evaluated to determine the adequacy of the model in representing the underlying structure of Access to Technology. The results indicated a Chi-Square/df value of 3.45, which exceeded the acceptable threshold of 3.0, suggesting that model refinement was necessary. Additionally, the Comparative Fit Index (CFI) was 0.870 and the Tucker-Lewis Index (TLI) was 0.852, both of which fell below the recommended benchmark of 0.90 for a well-fitting model. The Root Mean Square Error of Approximation (RMSEA) was 0.078, slightly above the desired cutoff value of 0.06, indicating a moderate but suboptimal model fit. Given these results, refinement of the model was deemed necessary to enhance its overall fit and unidimensionality.

Item Removal Process

To improve the model's performance, items with low factor loadings below 0.60 were removed through an iterative refinement process. The removal process focused on eliminating items that exhibited weak correlations with their respective sub-dimensions, thereby improving the overall validity of the construct. The analysis revealed that five items did not meet the minimum loading threshold, necessitating their exclusion from the final model. Specifically, within the Access to Hardware (AH) dimension, AH4 (loading = 0.55) and AH8 (loading = 0.57) were identified as weak indicators. Similarly, within the Use of Software (US) dimension, US3 (loading = 0.54) and US7 (loading = 0.58) failed to demonstrate a sufficient relationship with the latent variable. Furthermore, within the Usefulness of Technology (UT) dimension, UT2 (loading = 0.56) was also flagged for removal due to its inadequate contribution to the construct.

Following the removal of these five items, the revised model retained 19 items, ensuring that only strongly contributing indicators remained. The refined construct included eight items under Access to Hardware (AH1, AH2, AH3, AH5, AH6, AH7, AH9, AH10), seven items under Use of Software (US1, US2, US4, US5, US6, US8, US9), and four items under Usefulness of Technology (UT1, UT3, UT4, UT5). This refinement process allowed for greater construct validity, as the retained items more accurately reflected the conceptual structure of Access to Technology.

Final Measurement Model for Access to Technology Construct

After the removal of low-loading items, a revised CFA model was tested to examine whether these modifications resulted in improved model fit. The fit indices for the refined model demonstrated significant improvements, confirming that the changes were beneficial to the overall construct validity. The Chi-Square/df value decreased to 2.41, falling within the acceptable range below 3.0, indicating that the revised model exhibited a stronger fit to the data. The Comparative Fit Index (CFI) increased to 0.921, surpassing the recommended threshold of 0.90, and the Tucker-Lewis Index (TLI) improved to 0.908, also exceeding the critical value for acceptable model fit. Furthermore, the Root Mean Square Error of Approximation (RMSEA) was reduced to 0.061, which is within the desired range of 0.06 to 0.08, further confirming a well-fitting model.

The improvement in model fit indices indicates that the revised measurement model provides a more accurate and reliable representation of the Access to Technology construct. More importantly, all retained items in the revised model demonstrated factor loadings above 0.60, confirming their strong contributions to their respective sub-dimensions. The substantial increase in CFI and TLI values, combined with the reduction in RMSEA, underscores the model's enhanced ability to replicate the observed covariance matrix, strengthening its construct validity and internal consistency. These results confirm that the three sub-dimensions—Access to Hardware, Use of Software, and Usefulness of Technology—are well-defined and distinct constructs, allowing them to be effectively incorporated into the broader structural equation model.

The findings from the CFA validation process confirm that the Access to Technology construct is a reliable and valid measure of students' technological access, usage, and perceived usefulness. The iterative refinement process ensured unidimensionality, improved model fit, and retention of key items, aligning the construct with theoretical expectations. The final CFA model successfully validates the three sub-dimensions, establishing a strong statistical foundation for integrating this construct in subsequent analyses. This refined model not only ensures the statistical robustness of the construct but also enhances its applicability in studying the impact of technology access on student learning outcomes.

A summary of fit indices comparing the initial and final models is presented in Table 4.11, demonstrating the significant improvements achieved through the CFA refinement process.

Table 6: Comparison of the Initial and Final Measurement Model for Access to Technology Construct

Name of Index	Level of Acceptance	Initial Measurement Model	Final Measurement Model
Chi-Square	P-value >0.05	0.00 (N=385)	0.00 (N=385)
RMSEA	RMSEA <0.08 (acceptable)	0.078	0.061
TLI	TLI >0.90	0.852	0.908
CFI	CFI >0.90	0.870	0.921
Chi-Square /df	Chisq/df <3.0	3.45	2.41

Average Variance Extracted (AVE) and Composite Reliability (CR) were used to assess the validity and reliability of the Access to Technology construct, consisting of three sub-dimensions: Access to Hardware (AH), Use of Software (US), and Usefulness of Technology (UT). The factor loadings for retained items were above 0.70, confirming their strong contribution to their respective constructs. The CR values for all sub-constructs exceeded 0.90, indicating excellent internal consistency. Similarly, AVE values were all above 0.60, confirming adequate convergent validity. These results validate the measurement model and ensure the robustness of the Access to Technology construct for further structural analysis.

Table 7: AVE and CR for Access to Technology Construct

Sub-Construct	Item Label	Factor Loading	CR (above 0.6)	AVE (above 0.5)
Access to Hardware (AH)	AH1	0.812		
	AH2	0.784		
	AH3	0.765		
	AH5	0.798		
	AH6	0.742		
	AH7	0.789		
	AH9	0.758		
	AH10	0.741	0.915	0.632
Use of Software (US)	US1	0.825		
	US2	0.798		
	US4	0.776		
	US5	0.804		
	US6	0.735		
	US8	0.768		
	US9	0.791	0.902	0.621
Usefulness of Technology (UT)	UT1	0.829		
	UT3	0.784		
	UT4	0.742		
	UT5	0.762	0.89	0.615

Correlation Relationship Between Access to Technology and Academic Performance

This study sought to determine whether there is a relationship between Access to Technology (ATS) and Academic Performance (AP) among undergraduate students in the Digital Art Programme at public universities in Jilin Province, China. To determine this, Pearson's correlation analysis was conducted.

Table 8 displays the results of the analysis. With a p-value of below 0.05, significance is established. The analysis also revealed a moderate positive correlation between Access to Technology and Academic Performance ($r = 0.412$, $p < 0.01$).

According to Hair et al. (2018), correlation coefficients between 0.30 and 0.49 are considered moderate in strength, suggesting a meaningful, though not strong, association between the two variables. This result indicates that higher levels of access to technology are associated with better academic performance.

Table 8: Correlations between Access to Technology and Academic Performance

Dimension and Sub Dimensions	Academic Performance (AP)
Access to Technology (ATS)	Pearson Correlation
	Sig. (2-tailed)
Access to Hardware (AH)	Pearson Correlation
	Sig. (2-tailed)
Use of Software for Learning (US)	Pearson Correlation
	Sig. (2-tailed)
Usefulness of Technology (UT)	Pearson Correlation
	Sig. (2-tailed)

Overall, the findings confirm that Access to Technology is a significant factor in supporting the academic performance of students within the Digital Art Programme.

Discussion

These findings align with previous research emphasizing the critical role of technological resources in supporting student learning outcomes. As pointed out by Almarzooq et al. (2022), access to modern technology enhances students' academic engagement and facilitates the completion of coursework, leading to improved academic results. Furthermore, as noted by Sun and Gao (2021), the availability of digital tools and infrastructure can positively influence student performance, particularly in technology-intensive disciplines such as digital arts.

Further analysis of each dimension revealed important insights into how different aspects of technological access contribute to academic performance. Access to Hardware (AH) was found to have a significant positive correlation with academic performance. Students with consistent access to high-performance computers, graphic tablets, and other necessary hardware were better able to complete coursework efficiently, particularly assignments involving complex design and multimedia production. This finding is consistent with prior studies (Jones & Liu, 2021) that emphasize the critical role of hardware resources in creative disciplines like Digital Art.

Similarly, the dimension of Use of Software for Learning (US) demonstrated a strong positive relationship with academic achievement. Students who actively engaged with industry-standard software tools such as Adobe Creative Suite, Blender, and other digital platforms exhibited higher levels of skill development, creativity, and academic success. Regular use of advanced software not only enhanced technical proficiency but also supported students' ability to meet course requirements and participate in professional-level projects, aligning with the findings of Fuentes and Kim (2020).

Finally, Usefulness of Technology in Studies (UT) also showed a significant positive effect on academic outcomes, although the correlation was slightly lower compared to the other two dimensions. Students' perceptions of technology as an essential tool for learning—whether for accessing digital resources, participating in online learning, or collaborating on virtual projects—greatly influenced their motivation and engagement. Those who recognized the utility of technology were more likely to leverage digital tools effectively, contributing to better academic performance. This result supports previous research (Zhang & Tang, 2021) that highlights the importance of perceived usefulness in promoting active learning behaviors.

This study confirms that access to technology significantly influences the academic performance of Digital Art undergraduates in public universities in Jilin Province. Students with access to high-performance computers, industry-standard software, and stable internet connectivity tend to perform better academically. These findings align with previous research (Brown & Czerniewicz, 2019; Zhao & Xu, 2021), highlighting that technology enhances creativity, engagement, and learning efficiency. However, disparities in access, particularly between urban and rural institutions, remain a challenge, limiting equal learning opportunities.

This result provides empirical support for the theoretical framework of the study, which posits that technological resources are essential in fostering educational success in digitally driven academic environments.

Despite its contributions, this study has limitations, such as reliance on self-reported data and its focus on public universities in Jilin Province. Future research should adopt a longitudinal approach to assess long-term effects and incorporate qualitative insights into students' experiences. Overall, this study highlights the critical role of technology in Digital Art education and emphasizes the importance of bridging digital divides to ensure student success.

V. CONCLUSION

This study examined the relationship between access to technology and academic performance among Digital Art undergraduates in public universities in Jilin Province, China. The findings confirm that Access to Hardware (AH), Use of Software for Learning (US), and Usefulness of Technology in Studies (UT) each play a crucial role in supporting academic performance. Reliable hardware access enables students to complete complex digital tasks, while frequent software usage strengthens technical skills essential for success. Additionally, perceiving technology as useful motivates greater engagement in learning activities. Together, these dimensions highlight that both access and effective use of technology are vital for academic achievement in Digital Art education.

While this study provides valuable insights, it has limitations, including reliance on self-reported data and a focus on public universities in Jilin Province, which may limit its generalizability. Future research should explore longitudinal effects and incorporate qualitative methods to gain deeper insights into students' experiences with technology in Digital Art education.

In conclusion, access to technology is a crucial factor influencing academic performance in Digital Art programs. Bridging the digital divide through strategic investments and policy reforms will be essential to ensuring that all students, regardless of their background, have the resources needed to succeed in their academic and creative pursuits.

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