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Technology Adaption in Distance Teacher Training: The Impact of Demographic Factors on Learners' Technology Adaption

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Abstract

Understanding how demographic characteristics influence students' technology adaptation is crucial for effective online learning. This study explored the impact of these characteristics on distance education (DE) students' technology adaptation at a sub-Saharan African university. Using a descriptive survey design with a high-reliability score (Cronbach's Alpha = 0.898), data were collected from 200 DE students across 14 study centres. The study tested seven hypotheses, employing statistical analyses like ANOVA, t-tests, and post hoc tests. Results revealed that while gender and employment status did not significantly affect technology adaptation, age, academic programme, academic level, and study centre did. Students aged 26-35 adapted better, with those in Mathematics and English programs showing higher adaptation scores compared to those in the Postgraduate Diploma in Education (PGDE) program. Additionally, higher-level students and those from well-resourced study centres demonstrated superior adaptability. The study suggests providing targeted support based on age, academic programme, and study centre resources to enhance technology adaptation in DE. To further improve students' technology proficiency, the study recommends that DE institutions offer regular training sessions and workshops to help students navigate online platforms, use digital libraries, and maximize productivity tools.

Introduction

In an era marked by rapid technological advancement, the landscape of education is undergoing a profound transformation. As digital tools and platforms become increasingly integral to the learning process, it is imperative to explore the level of tech adaption and the diverse characteristics that influence the adaption process (Simonds & Brock, 2014). DE necessitates a high level of self-direction and responsibility, which some students may find difficult to manage (Sun, Hong, Huang, Dong, & Fu, 2023). Demographics of DE students have been found to have a significant influence on students' experiences and academic success (Egbo, Okoyeuzu, Ifeanacho & Onwumere, 2011; Suri & Sharma, 2013; Fleming, Becker & Newton, 2017; El Refae, Kaba & Eletter, 2021)) yet a few demographic characteristics have been studied in relation to DE for teacher training programmes in sub – Saharan African settings.

Demographic characteristics such as age, gender, employment status, program, academic level, and study centres, define individuals or populations in this study. Age reflects an individual's age group, while gender denotes biological differences between male and female. Employment status indicates whether a student is employed, unemployed, or self-employed. Programme refers to the specific academic course a student is enrolled in, while academic level signifies their progression, including undergraduate and postgraduate levels. In this study, there are four undergraduate levels and one post-graduate level. Study centre is the physical location where academic activities occur, with the institution, University of Education, Winneba (UEW), serving as a major institution for distance education and teacher training in Ghana. UEW's College for Distance and e-Learning (CODeL) offers various teacher training programs across 42 study centres nationwide. (University of Education, Winneba, 2021; Ghana-Business-News, 2022). The College offers instruction to students on weekends, with both students and lecturers convening at various study centres.

As noted by El Refae, Kaba and Eletter (2021), diverse demographic profiles influence technology adaption among DE students. This study addresses these lacunae by delving into the significance of demographics on technology adaption among DE students at UEW. The study endeavours to provide valuable insights for educators, policymakers, and stakeholders invested in the optimization of DE programs. Through a comprehensive exploration of the level of technology adaption among students as well as the demographic impact on these technology adaption behaviours, the study aims to chart a course toward enhanced learning experiences and improved outcomes for DE students in Sub-Saharan Africa.

Statement of the Problem

Technology-supported distance education has a long history, yet many universities in sub-Saharan Africa continue to depend heavily on traditional face-to-face learning methods for their distance programs (Seitebaleng, 2018; Ameyaw, 2022). This reliance presents significant challenges for distance education (DE) students, who are often working adults balancing multiple responsibilities, such as childcare and household duties, which greatly affect their ability to engage fully with their studies (Waterhouse, Samra, & Lucassen, 2022). Although the University of Education, Winneba (UEW) integrates technology into its educational framework, a significant gap remains in understanding how DE students effectively utilize digital resources for academic purposes (Bawacka & Kamdjoug, 2020). This gap points to the need for further research into the ways DE students engage with and benefit from technological tools in their learning processes. Additionally, while some institutions have initiated the integration of digital technologies, achieving widespread adaption remains a hurdle (Garlinska, Osial, Proniewska, & Pregowska, 2023) due to diverse demographic characteristics (Bubou & Job, 2022). Bubou and Job (2022) highlight the significant impact of demographics on technology adaption among DE students, yet certain factors remain understudied. This study addresses these overlooked demographics, aiming to develop strategies that enhance technology integration and support the learning needs of DE students.

Purpose of the Study

The purpose of this study is to explore the level of technology adaption among DE students at UEW, with a specific focus on how demographic characteristics influence their technology adaption.

Research Hypothesis

Two research questions that guided the study were hypothesized to determine if there was any significant level of technology adaption for DE students' academic activities as well as the significance of their demographic characteristics on their technology adaption. Seven hypotheses were formulated from the research questions. The hypotheses were tested using statistical methods such as ANOVA, t-test, post hoc analysis.

Level of Technology Adaption of DE Students

1. H_{01}: There is no significant level of technology adaption by distance education (DE) students in sub-Saharan African distance education programs.

Demographic Characteristics Effect on Technology Adaption of DE Students

2. ***Age:*** H_{02}: There is no significant difference in technology adaption between younger learners and older learners.
3. ***Gender:*** H_{03}: There is no significant difference in technology adaption between male and female learners in distance teacher training programs.
4. ***Employment Status:*** H_{04}: There is no significant difference in technology adaption between employed and unemployed learners in distance teacher training programs.
5. ***Programme:*** H_{05}: There is no significant difference in technology adaption between students' programmes in distance teacher training programs.
6. ***Education Level:*** H_{06}: There is no significant difference in technology adaption between undergraduate and post-graduate students in distance teacher training programs.
7. ***Study Centre:***H_{07}: There is no significant difference in technology adaption between students from different study centres.

Literature Review

This review aims to provide insights into the level of technology adaption among DE students and the demographic characteristics influencing technology adaption.

Level of Technology Adaption among Distance Education Students

In recent years, technology has played a pivotal role in transforming the landscape of education, particularly in the realm of distance education (Bawacka & Kamdjoug, 2020). Exploring the current level of technology adaption among DE students is crucial for academic success. One key factor influencing technology adaption among DE students is access to digital resources and infrastructure. Studies have shown that limited access to technology or inadequate internet connectivity may affect the level of technology adaption among students (Garlinska et al., 2023).

Additionally, individual characteristics such as age, prior experience with technology, and self-efficacy play significant roles in determining students' readiness to adapt digital tools for educational purposes (Bubou & Job, 2022). In a related study, Mitzner et al. (2010) examined the attitudes of older adults towards technology use. The study revealed that older adults generally have positive attitudes towards technology, but their actual use is often limited by factors such as perceived complexity and lack of familiarity.

External factors such as work and family commitments may also impact students' ability to dedicate time to learning and mastering new technologies. Lee and Choi (2017) explored the factors that influence higher-order thinking in technology-enhanced learning environments. Their research identified that learner characteristics, such as motivation, self-regulation, and prior knowledge, significantly impact the effectiveness of technology in fostering critical thinking skills. The study emphasizes that while technology can provide opportunities for enhanced learning, its success largely depends on the learners' ability to engage with these tools meaningfully. Further studies have also shown that effective utilization of technology can enhance engagement, collaboration, and knowledge retention (Shrader, Wu, Owens, & Santa Ana, 2016; Ameyaw, 2022). As technology continues to shape the landscape of education, it is essential for institutions and educators to prioritize efforts to support students in effectively adapting to digital tools and platforms.

The Effects of Demographic Factors of Distance Education Students on their Technology Adaption

Demographic factors have been found to have significant effects on distance learners' adaption to technology. Egbo et al. (2011), Suri and Sharma (2013), Bubou and Job (2022) shed light on technology adaption and the influence of demographic variables of DE students in an online learning system. Moreover, prior studies have also suggested that demographic characteristics such as age, gender, and income can have an impact on student adaption to technology (Christmann, 2017; Amparo et al., 2018). Bubou and Job (2022) revealed that male respondents have higher e-learning adaption than their female counterparts in online systems. However, some studies by Egbo, Okoyeuzu, Ifeanacho and Onwumere (2011); Suri and Sharma (2013); Raman, Don, Khalid and Rizuan (2014) did not find any significant relation between gender and technology adaption. Furthermore, recent studies suggest a potential link between higher computer anxiety among girls and the gender biases of teachers therefore, given the prevalence of gender-related barriers reported in university settings, it is conceivable to hypothesize that males may possess certain advantages over females in their skills, perspectives, and utilization of educational technology (Megalokonomou & Lavy, 2023).

Moreover, research by Simonds and Brock (2014); Morin, Fard, Saade (2019) and Staddon (2020) also revealed a correlation between student age and their preference for specific online learning activities. Simonds and Brock (2014) revealed that older students displayed a notably stronger inclination towards watching videos of professors lecturing, whereas younger students leaned towards more interactive learning methods. Moreover, Morin, Fard, and Saade (2019) revealed that older students exhibit greater confidence in computer proficiency and learning skills compared to their younger counterparts as they demonstrate higher levels of motivation, positive attitudes, and reduced anxiety towards technology. Staddon investigated the technological engagement of mature students compared and found them to adapt more to technology than their younger counterparts. In contrast, findings from

Fleming, Becker, and Newton (2017) suggest that, despite the often-espoused stereotype, age is not a significant factor impacting either future use intentions or satisfaction with digital literacy.

Studies by Zhao and Mei (2016), Waterhouse, Samra, and Lucassen (2022) investigated the significance of employment status of DE students and their motivation in an online system. Zhao and Mei (2016) found that online learners’ learning motivation was affected by distance students' characteristics such as employment status. Waterhouse, Samra, and Lucassen (2022) also found that DE students with coresident children were less likely to be satisfied with their learning experience.

Furthermore, research by Morris et al. (2015) highlights how employment status influences learners’ dedication in adapting to online learning environments, showing that unemployed learners tend to complete more content. Similarly, Cisel (2014) study underscores the heightened learning ambitions of unemployed learners, who set higher targets and cover more material. Shrader et al. (2016) analysis of six online learning platforms on Coursera emphasizes the diverse engagement levels across employment statuses, with employed, unemployed, and retired learners demonstrating a penchant for watching lecture videos.

The embrace of online learning varied depending on students’ academic levels, with higher-level undergraduates and postgraduates displaying greater adaptability compared to their freshman and sophomore counterparts (Khalil et al., 2020; Klein et al., 2021; Yu, 2021). This discrepancy may stem from newer students’ unfamiliarity with university systems and culture, underscoring the importance of readiness for online instruction. Moreover, a study by Lazar, Panisoara and Panisoara (2020) revealed that anxiety negatively influences the perception of utility and consequently, the intention to use technology, particularly among master’s students. In contrast, undergraduates may face less anxiety or perceive fewer barriers, which could explain their higher adaptability. This could imply that postgraduate students, who might have more specialized or demanding academic goals, are more sensitive to perceived barriers and anxieties surrounding technologies.

While conducting a comprehensive review of the literature, it was observed that there is a notable lack of research focusing on the significance of program types and study centres on the adaption to technology among DE students. Despite extensive efforts to locate relevant studies, including searches in academic databases, journals, and institutional repositories, no empirical studies directly addressing this aspect of technology adaption in the context of distance education were identified. This gap in the literature suggests a critical area for future research to explore, particularly considering the potential impact of program structures and study centre environments on students’ engagement with technology in distance learning settings.

Methodology

Research Design

The study employed a descriptive survey design, utilising a convenience sample of 200 distance education students from the University of Education, Winneba, during the 2022/23 academic year.

Study Group

The University of Education, Winneba offers distance programs through forty-two (42) study centres across the country. Fourteen (14) of these centres were used for the study. Out of a total of 200 participants, 115 (57%) were male and 85 (43%) were female. The sample consisted of 195(97.5%) undergraduate students and 5(2.5%) post-graduate students. The age range of the participants was 15-25 years (13% (n=26)), 26-35 years (60.5% (n=121)), 36-45 years (18.5% (n=37)) and above 46 years (8% (n=16)).

Sampling Technique & Data Collection

Convenience sampling was used to collect data on demographic factors influencing technology adaption in distance teacher training. The survey, distributed via Google Forms, was voluntary and aimed to reach a geographically dispersed population efficiently. While this method may not fully represent the entire student population, widespread distribution and reminders to centre administrators helped encourage diverse participation. Sensitivity analysis confirmed the sample's adequacy and representativeness, capturing various demographic groups crucial for understanding technology adaption among distance education students.

Instrument, Validity and Reliability

A questionnaire adapted from Bawacka and Kamdjougb (2020) was used, comprising four sections to gather data on students' demographics and technology adaption. To ensure validity, the questionnaire was reviewed by other lecturers and experts for face and content validity, and responses were compared with those from a validated instrument for criterion validity. Reliability was established through a pilot study, refining the questionnaire based on feedback from 20 distance education students. The final instrument achieved a high-reliability coefficient of .898 (Cronbach's Alpha), indicating strong consistency and dependability.

Results

Table 1 shows the various demographic characteristics of the participants. The ages of the students were in 4 categories with most (N=121, 60.5%) of the students in the age range of 26-35 years. Majority (N=115, 57%) of the students were males and most (N=154, 77%) of the students were employed. There were eight (8) programmes in all with Bachelor of Business Administration (BBA) having the highest number of students. Out of the 14 study centres studied, majority (N=90, 45%) of the students were from the Winneba study centre.

Table 2 shows participants' responses to technology adoption behaviour of distance items on the questionnaire. From Table 2, students have a strong inclination towards using digital technologies to exchange information with their friends and classmates (M = 4.43, SD = 0.830), send assignments to lecturers with digital technologies (M = 4.05, SD = 1.031), collaborate on group projects and assignments with colleagues (M =4.17, SD =0.755), make better decisions during school projects (M = 4.28, SD = 0.746) and also solve problems that may arise with academic work (M = 4.17, SD = 0.823). The mean scores for these activities range from 4.05 to 4.28, with standard deviations ranging from 0.746 to 1.031 indicating relatively low variability in how participants adapt to technology. This suggests a consistent pattern of active engagement with digital tools across different academic tasks, reflecting the importance of technology in facilitating communication, collaboration, decision-making, and problem-solving within educational contexts.

Table 1. Demographic Factors of Distance Education Students

Demographic Factors	Item	Number (N)	%
Age	15-25	26	13
	26-35	121	60.5
	36-45	37	18.5
	46 above	16	8
Gender	Male	115	57
	Female	85	43
Employment Status	Employed	154	77
	Unemployed	46	23
Programme	Basic Education	40	20.0
	Early Childhood	17	8.5
	Early Grade	5	2.5
	Business Administration (BBA)	85	42.5
	Mathematics	22	11.0
	English	20	10.0
	Social Studies	7	3.5
	Post-Graduate Diploma in Education (PGDE)	4	2.0
Academic Level	100	5	2.5
	200	20	10.0
	300	71	35.5
	400	99	49.5
	600	5	2.5
Study Centre	Accra academy (College of Education)	16	8
	Accra College (College of Education)	3	1.5
	Accra St. Johns (Senior High School)	17	8.5
	Accra Wesley (Accra Wesley Girls SHS)	6	3
	Cape coast (Technical Institution)	9	4.5
	Ho (Technical University)	25	12.5
	Kasoa (Gateway Primary School Complex)	3	1.5
	Kumasi Aamusted (Polytechnic University)	2	1
	Tamale Batco (Bagabaga College of Edu.)	2	1
	Techiman (Good Shepherd Int. School)	5	2.5
	Tema (Presby S.H.S., community 11)	12	6
	Wa (N. J. Ahmadiyya College of Edu.)	5	2.5
	Winneba (University of Education, winneba)	90	45
	Yendi (Senior High School)	2	1

Table 2. Technology Adaption Behaviour of Distance Education Students

TECHNOLOGY ADAPTION	**SA (5) N (%)**	**A (4) N (%)**	**N (3) N (%)**	**D (2) N (%)**	**SD (1) N (%)**	**M**	**SD**
I frequently use digital technologies such as my phone or laptop to exchange information with friends and classmates	116 (58)	66 (33)	11 (5.5)	3 (1.5)	4 (2)	4.43	.830
I regularly utilize digital technologies (such as my phone or laptop) to send my assignments to lecturers	80 (40)	76 (38)	23 (11.5)	16 (8)	5 (2.5)	4.05	1.031
I actively engage digital technologies to collaborate on group projects and homework with my classmates	69 (34.5)	101 (50.5)	25 (12.5)	4 (2)	1 (0.5)	4.17	.755
I often rely on information obtained online to inform my decision-making process for school projects.	89 (44.5)	82 (41)	26 (13)	3 (1.5)	0 (0.0)	4.29	.746
I frequently use online information accessed through technology (phone, laptop) to solve problems related to my schoolwork	78 (39)	88 (44)	26 (13)	7 (3.5)	1 (0.5)	4.18	.823

Further, one-way analysis of variance (ANOVA) with Post Hoc test, and t-Test were conducted to examine whether there are significant associations between Technology Adaption and the demographic variables at a significant value of 0.05. Table 3 reveals the descriptive Statistics for Technology Adaption Behaviour by students 'age' which shows that older students tend to have slightly higher mean scores for technology adaption compared to younger students. For instance, the mean score for 36-45 age group is 3.9550, suggesting that, on average, students in this age bracket have a relatively high level of technology adaption.

Table 3. Descriptive Statistics for Technology Adaption Behaviour by Age

Technology Adaption				
Age	N	Mean	Std. Deviation	Std. Error
15-25	26	3.6859	.40367	.07917
26-35	121	3.8154	.56675	.05152
36-45	37	3.9550	.49791	.08186
46 Above	16	3.5417	.48113	.12028
Total	200	3.8025	.53678	.03796

The analysis for the significance of age on technology adaption behaviour is presented below (see Table 1 for the distribution of students' demographic factors).

Significance of Age on Technology Adaption

Table 4 presents the results of the ANOVA test, examining the significance of age on technology adaption. Age was found to have a significant ($F(3, 196) = 2.758$, $p < .044$) effect on technology adaption hence the H_{02} is rejected meaning that there is significant difference between the different age groups in how they adapt technology for academic purposes.

Table 4. Significance of Age on students' Technology Adaption

ANOVA					
	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	2.322	3	0.774	2.758	0.044
Within Groups	55.015	196	0.281		
Total	57.338	199			

Table 5 presents the results of post hoc tests using Tukey's HSD test.

Table 5. Post Hoc Test of Specific Group Means

Multiples comparisons					
	AGE	**1**	**2**	**3**	**4**
1	15-25				
2	26-35	.12953			
3	36-45	.26906	.13953		
4	46 Above	-.14423	-.27376	-.41329*	

*The mean difference is significant at a 0.05 level

The results revealed no significant differences in technology adaption scores between the youngest cohort, aged 15-25, and any other age group in this comparison. These finding challenges conventional notions regarding the technological prowess of younger individuals, suggesting that age may not be the sole determinant of technology adaption among DE students. Likewise, no significant disparities in technology adaption scores were found between the 26-35 age group and the others, reaffirming the notion of a relatively uniform technological landscape across these mid-range age brackets. However, a notable contrast emerged when comparing the age ranges of 36-45 with 46 and above.

Significantly, lower technology adaption scores were observed among the oldest age range. This means that while age may exert some influence on technology adaption, the impact may be less pronounced than previously assumed. Rather, factors beyond age, such as individual experiences, attitudes towards technology, and access to resources, likely play a more pivotal role in shaping technology adaption behaviours. With this, educators and policymakers can devise more effective strategies to foster inclusive and equitable technological environments conducive to learning and growth across all age groups (see Figure 1).

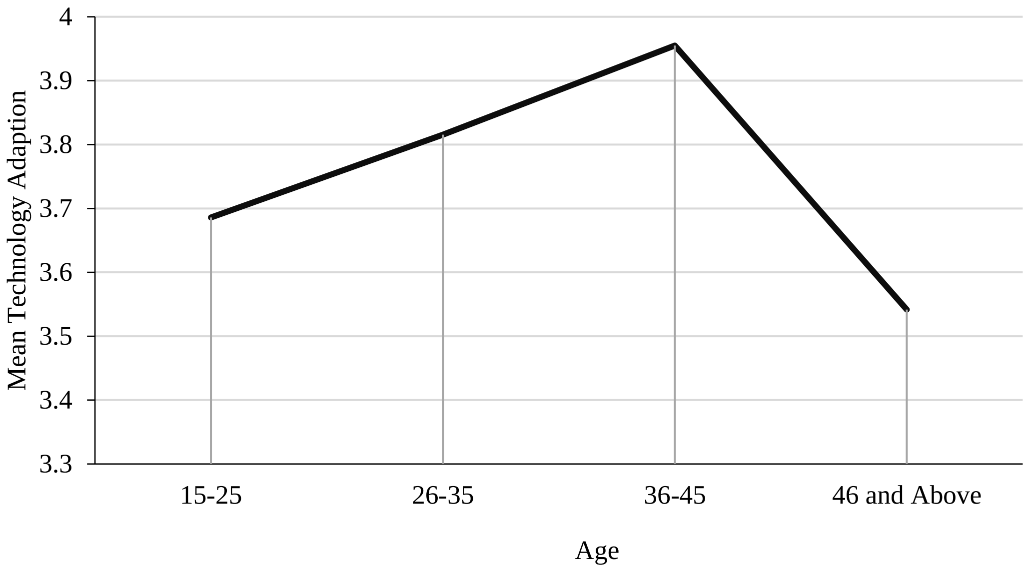

Figure 1 Age Significance on Technology Adaption

Significance of Gender on Technology Adaption

The group statistics for gender offer insights into the technology adaption scores of male and female DE students. Interestingly, the analysis reveals a marginal difference in mean technology adaption scores between male and female students. Specifically, male students exhibit a slightly higher mean technology adaption score (3.82) compared to their female counterparts (3.80). However, this discrepancy is not deemed statistically significant, as evidenced by the non-significant p-value. The t-value further supports this conclusion, indicating that the observed difference in means is likely due to chance variation rather than a true disparity based on gender. The findings support the Null Hypothesis H_{03}, indicating that gender does not significantly influence technology adaption scores among the DE students ($t = 0.500$, $df = 198$, $p = 0.426$).

Table 6. Significance of Gender on Technology Adaption

t-tests								
	Gender	**N**	**Mean**	**Std. Deviation**	**Mean Difference**	**df**	**t**	**Sig.**
Technology	Male	115	3.82	0.56	0.038	198	0.500	0.426
Adaption	Female	85	3.80	0.51				

Significance of Employment Status on Technology Adaption

Table 7 reveals a notable contrast in mean technology adaption scores between the two groups. Specifically, employed students exhibit a higher mean technology adaption score (3.87) compared to their unemployed counterparts (3.56). Despite this difference, the statistical analysis indicates that the observed disparity is not statistically significant, as evidenced by the non-significant p-value of 0.79. The t-value of 3.57 further supports this conclusion, suggesting that any observed variation in technology adaption scores based on employment status is likely due to random chance rather than a meaningful difference (t=3.57, df=198, p=0.79). Hence, the Null Hypothesis H_{04} holds.

Table 7. Significance of Employment Status on Technology Adaption

t-test								
	Employment Status	**N**	**Mean**	**Std. Deviation**	**Mean Difference**	**df**	**t**	**Sig.**
Technology	Employed	154	3.87	0.52	0.31	198	3.57	0.79
Adaption	Unemployed	46	3.56	0.51				

The descriptive statistics for various academic programs shed light on the technology adaption levels of DE students across different disciplines (see Table 8).

Table 8. Descriptive Statistics for Technology Adaption Behaviour by Programme

Descriptive				
	N	**Mean**	**Std. Deviation**	**Std. Error**
Basic Education	40	3.475	0.483	0.076
Early Childhood	17	3.833	0.503	0.122
Early Grade	5	3.700	0.462	0.207
Business Administration (BBA)	85	3.776	0.435	0.047
Mathematics	22	4.349	0.199	0.042
English	20	4.350	0.247	0.055
Social Studies	7	3.309	0.539	0.204
Post-Graduate Diploma (PGDE)	4	2.750	0.441	0.220
Total	200	3.803	0.537	0.038

Notably, the analysis reveals a wide spectrum of mean technology adaption scores among students enrolled in distinct programs. For instance, the Mathematics and English programs emerge as frontrunners in technological proficiency, boasting the highest mean technology adaption scores of 4.349 and 4.350, respectively. This suggests a robust utilization of digital tools and resources within these academic domains, possibly driven by the nature of coursework and pedagogical practices. Conversely, the PGDE program stands out with the lowest mean technology adaption score of 2.750, indicating a relative lack of technological fluency among students in this program. This disparity may stem from factors such as program structure, instructional strategies, or inherent differences in student demographics and backgrounds.

Significance of Programme on Technology Adaption

The ANOVA results unveil significant ($F(7, 192) = 18.509$, $p < .001$) disparities in technology adaption scores among different academic programs. This suggests that the choice of program exerts a considerable influence on students' proficiency and utilization of technology in the context of distance education.

Table 9. Analysis of Variance test (ANOVA[a]) for Significance of Programme on Technology Adaption

ANOVA					
	Sum of Squares	**df**	**Mean Square**	**F**	**Sig.**
Between Groups	23.102	7	3.30	18.509	.000
Within Groups	34.236	192	0.178		
Total	57.338	199			

However, merely identifying these variations through ANOVA provides a broad overview. To delve deeper into the specific differences between program categories, post hoc tests were used (see Table 10).

Table 10. Post Hoc Test of Specific group means

Multiple Comparisons								
	Programme	**1**	**2**	**3**	**4**	**5**	**6**	**7**
1	Basic Education							
2	Early Childhood	0.358						
3	Early Grade	0.225	-0.133					
4	BBA	0.302*	-0.057	0.077				
5	Mathematics	0.874*	0.515*	0.649*	0.572*			
6	English	0.875*	0.517*	.6500*	0.5735*	0.0015		
7	Social Studies	-0.165	-0.524	-0.391	-0.467	-1.039*	-1.041*	
8	PGDE	-0.725*	-1.083*	-.950*	-1.027*	-1.599*	-1.600*	-0.559

*The mean difference is significant at 0.05 level

From the post hoc analysis, while some programs exhibited high levels of technology adaption, others lagged behind, underscoring the diverse technological landscapes within distance education. For example, the Mathematics and English programs exhibited significantly higher technology adaption scores compared to the Basic Education, Early Childhood, and Early Grade programs. The Null Hypothesis H_{05} is therefore rejected (see Figure 2).

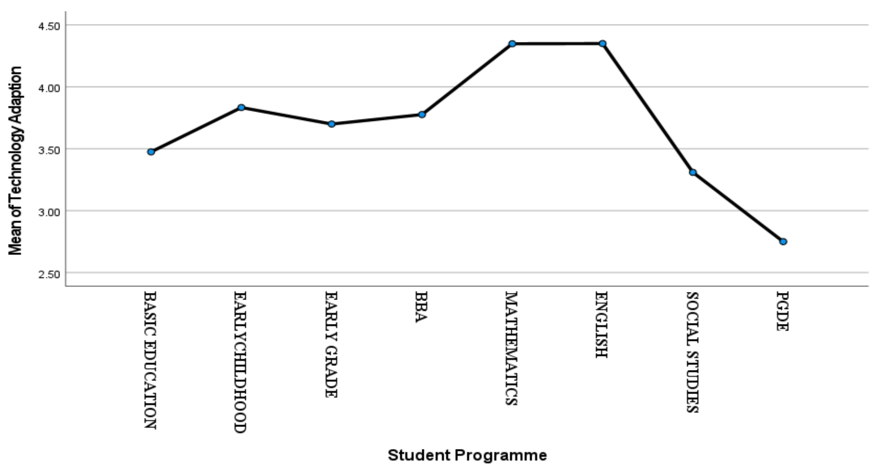

Figure 2. Significance of Students' Programme on their Technology Adaption

Table 11 reveals variations in mean technology adaption scores across academic levels.

Table 11. Descriptive Statistics for Technology Adaption Behaviour by Academic Level of DE students

Descriptive				
	N	**Mean**	**Std. Deviation**	**Std. Error**
100	5	3.467	0.649	0.290
200	20	3.425	0.395	0.088
300	71	3.793	0.489	0.058
Current level 400	99	3.939	0.509	0.051
600	5	3.067	0.805	0.359
Total	200	3.802	0.537	0.038

Students at academic level 400 exhibited the highest mean technology adaption score (3.939), indicating a relatively higher proficiency in utilizing technology in their learning endeavours. Conversely, students at level 600 displayed the lowest mean technology adaption score (3.067), suggesting a lower level of technological fluency in this cohort.

Significance of Academic Level on Technology Adaption

The ANOVA results indicate significant ($F(4, 195) = 7.885$, $p < .001$) differences in technology adaption scores among academic levels (see Table 12). This suggests that the academic level of students significantly influences their proficiency of technology in the context of distance education. Therefore, Null Hypothesis H_{06} is rejected. The between-groups variance is 7.982, indicating substantial differences in mean technology adaption scores across academic levels.

Table 12. ANOVA[a] of Significance of Academic Level on Technology Adaption Behaviour

ANOVA					
	Sum of Squares	**df**	**Mean Square**	**F**	**Sig.**
Between Groups	7.982	4	1.996	7.885	.000
Within Groups	49.355	195	.253		
Total	57.338	199			

In comparing Academic Levels in a Post Hoc test (see Table 13), level 200 does not significantly differ from level 100 (p = 1.000), however, for the comparison between 200 and 300, the mean difference is -0.36843* with a standard error of 0.12736, and the p-value is 0.034, indicating a significant difference in technology adaption scores between these two groups. Academic level 300 exhibits significantly higher technology adaption scores compared to levels 100 (p = 0.626) and 200 (p = 0.034). Academic level 400 displays significantly higher technology adaption scores compared to levels 100 (p = 0.246) and 200 (p = 0.001) and academic level 600 demonstrates significantly lower technology adaption scores compared to levels 100 (p = 0.718), 200 (p = 0.613), 300 (p = 0.17), and 400 (p = 0.002).

Table 13. Post Hoc Test of Specific Group Means

Multiple Comparisons						
	Academic Level	**1**	**2**	**3**	**4**	**5**
1	100					
2	200	-.04167				
3	300	.32676	.36843*			
4	Current Level 400	.47273	.51439*	.14597		
5	600	-.40000	-.35833	-.72676*	-.87273*	

Academic level 400s are students in their final years of study and this indicates that students in this level tend to exhibit greater proficiency and utilization of technology, as evidenced by their higher mean technology adaption scores. Conversely, students at lower academic levels display comparatively lower levels of technological fluency (see Figure 3).

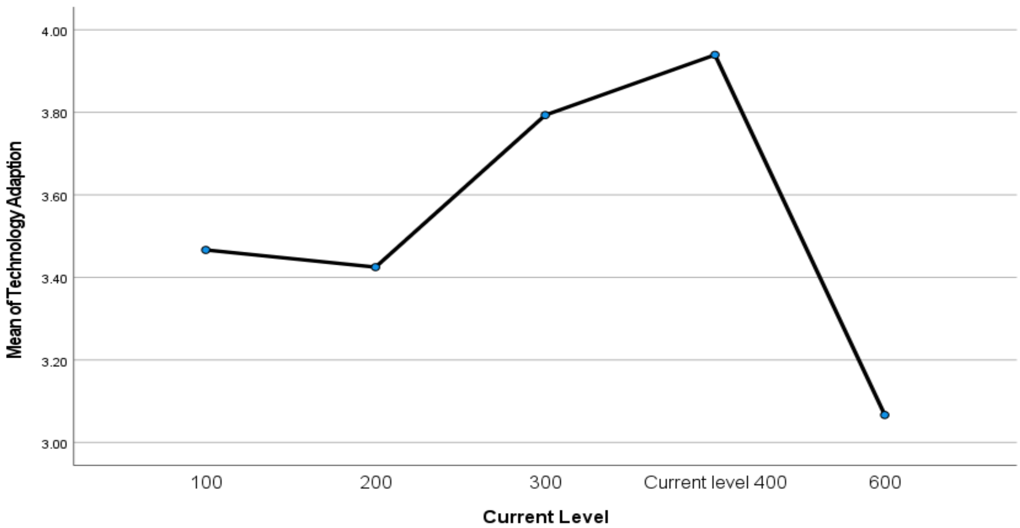

Figure 3. Significance of Academic Level on Technology Adaption

Significance of Study Centres on Technology Adaption

Table 14 reveals variations in mean technology adaption scores across study centres. Students at the HO study centre exhibited the highest mean technology adaption score (4.2319), indicating a relatively higher proficiency in utilizing technology in their learning endeavours. This centre has different partners and initiatives aimed at advancing technical and vocational education. These activities include developing and implementing precision quality programs, organizing entrepreneurship competitions, participating in work-based learning projects, and collaborating with other institutions for training and grant proposals. These initiatives showcase the adaptability of the centre to technology and innovation, as it embraces partnerships and programs geared towards enhancing learning experiences and opportunities through technological advancements. Conversely, students at the TAMALE BATCO study centre displayed the lowest mean technology adaption score (2.9167), suggesting a lower level of technological fluency.

Table 14. Descriptive Statistics for Technology Adaption Behaviour by Study Centre

Descriptive				
	N	**Mean**	**Std. Deviation**	**Std. Error**
ACCRA ACADEMY (College of Education)	16	3.4688	.57484	.14371
ACCRA COLLEGE (College of Education)	3	3.6667	.16667	.09623
ACCRA ST. JOHNS (Senior High School)	17	3.9412	.53014	.12858
ACCRA WESLEY (Accra Wesley Girls SHS)	6	4.0278	.56191	.22940
CAPE COAST (Technical Institution)	9	3.9074	.60157	.20052
HO (Technical University)	23	4.2319	.44873	.09357
KASOA (Gateway Primary School Complex)	3	3.6111	.91793	.52997
KUMASI AAMUSTED (Polytechnic University)	2	3.3333	.23570	.16667
TAMALE BATCO (Bagabaga College of Edu.)	2	2.9167	1.06066	.75000
TECHIMAN (Good Shepherd Int. School)	5	3.6000	.38370	.17159
TEMA (Presby S.H.S., community 11)	12	3.6806	.38572	.11135
WA (N. J. Ahmadiyya College of Edu.)	5	3.7000	.34157	.15275
WINNEBA (University of Education, winneba)	90	3.8407	.44617	.04703
YENDI (Senior High School)	2	3.0000	.70711	.50000
Total	195	3.8248	.52206	.03739

Table 15 indicates significant (F (13, 181) = 3.527, $p < .001$) differences in technology adaption scores among academic levels, therefore Null hypothesis H_{07} is rejected. The Post Hoc Tukey's (HSD) test identifies which study centres yield statistically distinct levels of technology adaption among students, offering more conducive environments or resources for fostering technological proficiency. In Table 16, the mean difference in the comparison between Ho and Accra Academy, Tamale Batco, Winneba and Yendi is significant at the 0.05 level ($p < 0.05$). This means that there is a significant difference in the mean technology adaption scores between students from Ho and the other 5 centres.

Table 15. ANOVA of Significance of Study Centre on Technology Adaption

ANOVA					
	Sum of Squares	**df**	**Mean Square**	**F**	**Sig.**
Between Groups	10.687	13	.822	3.527	.000
Within Groups	42.188	181	.233		
Total	52.875	194			

In comparing the individual centres, ACCRA WESLEY demonstrates notably higher technology adaption compared to ACCRA COLLEGE and ACCRA ST. JOHNS, underscoring disparities within the same geographical region. Similarly, the HO study centre stands out with significantly higher technology adaption scores compared to most other centres, reflecting potential differences in resources, infrastructure, or instructional approaches. Conversely, the TAMALE BATCO study centre presents a contrasting picture, displaying significantly lower technology adaption scores across pairwise comparisons. This highlights the challenges faced by students in this centre in their technological fluency. Furthermore, other study centres exhibit varying levels of significance in pairwise comparisons, indicating nuanced differences in tech adaption across different environments.

Table 16. Post Hoc Test of Specific Group Means

POST HOC TEST/ Multiple Comparisons														
	STUDY CENTRE	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**
1	**ACCRA ACADEMY** (College of Education)													
2	**ACCRA COLLEGE** (College of Education)	.198												
3	**ACCRA ST. JOHNS** (Senior High School)	.4724	.275											
4	**ACCRA WESLEY** (Accra Wesley Girls SHS)	.559	.361	.0866										
5	**CAPE COAST** (Technical Institution)	.439	.241	-.034	-.12									
6	**HO** (Technical University)	.763*	.565	.291	.204	.324								
7	**KASOA** (Gateway Primary School Complex)	.142	-.056	-.33	-.417	-.296	.621							
8	**KUMASI AAMUSTED** (Polytechnic University)	-.135	-.333	-.608	-.694	-.574	-.899	-.278						
9	**TAMALE BATCO** (Bagabaga College of Edu.)	-.552	-.75	-1.03	-1.11	-.991	-1.32*	-.694	-.417					
10	**TECHIMAN** (Good Shepherd Int. School)	.131	-.067	-.341	-.428	-.307	-.631	-.011	.267	.683				
11	**TEMA** (Presby S.H.S, community 11)	.212	.014	-.261	-.347	-.227	-.551	.069	.347	.764	.081			
12	**WA** (N. J. Ahmadiyya College of Education)	.231	.033	-.241	-.328	-.207	-.532	.089	.367	.783	.10	.019		
13	**WINNEBA** (University of Education, winneba)	.372	.174	-.10	-.187	-.067	-.391*	.229	.507	.924	.241	.160	.141	
14	**YENDI** (Senior High School)	-.469	-.667	-.941	-1.03	-.907	-1.23*	-.611	-.333	.083	-.600	-.681	-.700	-.841

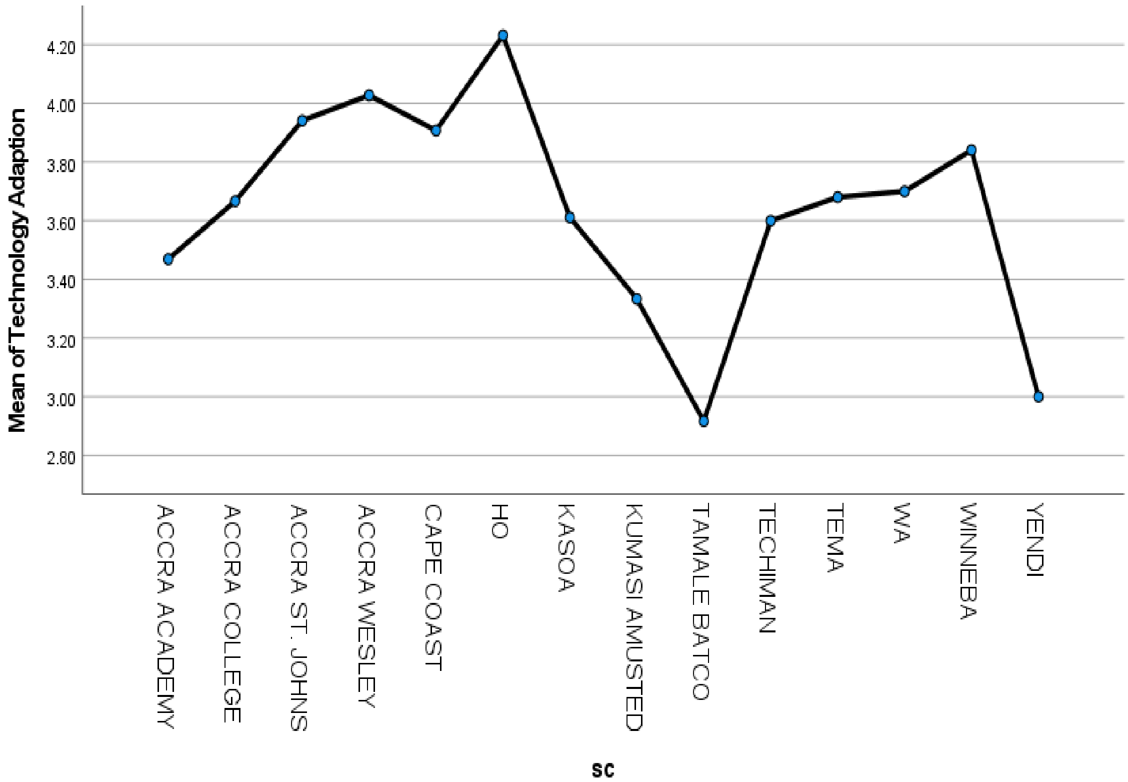

Figure 4. The Significance of the Study Centres on Technology Adaption

Discussion

Based on the findings in the study, DE students exhibit a moderate to high level of technology adaption, particularly in utilizing digital tools for various academic purposes. The strong inclination towards using digital technologies for exchanging information with peers, sending assignments to lecturers, collaborating on group projects, making decisions during school projects, and solving academic-related problems suggests a robust integration of technology into their academic endeavours. The mean scores ranging from 4.05 to 4.28 indicate that these activities are consistently facilitated by digital technologies among the student population.

Additionally, the relatively low standard deviations suggest minimal variability in responses, indicating a widespread and uniform adaption of digital tools across different academic tasks. These findings highlight the significant role of technology in facilitating communication, collaboration, decision-making, and problem-solving within educational contexts. The students' strong reliance on digital technologies for these activities showcases the importance of incorporating technology-enhanced learning experiences in DE programs to effectively meet the evolving needs of students and enhance their overall academic experiences. These findings align with studies from Vlachopoulos and Makri (2019); Chen, Landa, Padilla and Yur-Austin (2021); Bawacka and Kamdjoug (2020) who found high levels of technology adaption by students for various educational purposes.

From the ANOVA test, age was statistically significant. However, the HSD test showed no significant differences in technology adaption scores between the younger age groups and the older ones suggesting that mature students adapt to technology more than younger adults. Moreover, a significant difference was observed between the 36-45 and the 46 and above age group, indicating that the latter had significantly lower technology adaption scores compared to the former. These findings suggest that while there may be some variation in technology adaption across age groups, the disparities are not statistically significant except for the contrast between the 36-45 and 46 and above age groups. This study contrasts with study from Fleming, Becker and Newton (2017) which saw no significance of age in technology adaption behaviours among diverse age groups but aligns with studies from Simonds and Brock (2014); Morin, Fard, Saade (2019) and Staddon's (2020) research which supported the technological engagement of mature students compared to their younger counterparts. According to Staddon, despite mature students employing fewer technologies and utilizing them less frequently, they boast a wealth of experience with technology over their lifetimes. This extended exposure suggests that while they may not adopt new technologies as readily as younger students, they possess a deep-rooted familiarity with technological tools.

Additionally, Lee and Choi (2017) reveal the transformative potential of technology for mature students, enabling them to embrace advanced learning approaches. Despite Czaja et al.'s (2006) observation that older individuals exhibit lower engagement with technology compared to their younger counterparts, Mitzner et al. (2010); Lazar, Panisoara, & Panisoara (2020) reveal that when older individuals perceive technology as valuable and useful, their motivation to engage with and learn from it surges. Moreover, the analysis shows a slightly higher mean technology adaption score (3.82) for male students than that of female students (3.80). However, the difference in means is not statistically significant ($p = 0.507$), as indicated by the t-value of 0.500. This suggests that there is no significant gender-based discrepancy in technology adaption scores among the students sampled. This implies that gender may not play a significant role in influencing technology adaption among DE students at the university. In this study gender does not affect distance students’ adaption to technology. This study is consistent with studies from Egbo, Okoyeuzu, Ifeanacho, and Onwumere (2011); Suri and Sharma (2013); Raman, Don, Khalid and Rizuan (2014) who did not find any significant difference between male and female in their internet adaption. Therefore, we retain the null hypothesis stating that there is no significant difference in technology adaption between male and female learners in distance teacher training programs.

The group statistics for employment status show that employed students generally have a higher technology adaption score compared to unemployed students. However, this difference is not statistically significant. This suggests that there is no significant discrepancy in technology adaption scores based on employment status among the students sampled. This indicates that there is no relationship between employment status and technology adaption among DE students, therefore, we retain the null hypothesis stating that there is no significant difference in technology adaption between employed and unemployed learners in distance teacher training programs. Further analysis may be needed to understand the nature of this relationship.

Unlike gender and employment status, there is a significant association between technology adaption and student programmes. This suggests that different student programs may influence technology adaption differently among the students. We therefore reject the null hypothesis. This aligns with findings from Lazar, Panisoara, & Panisoara (2020). Understanding these differences could be crucial for tailoring technology integration strategies for different programs. This suggests a divergence in technological engagement between disciplines that may have implications for instructional design and support mechanisms tailored to address the unique needs of students in different programs. Furthermore, the significance of these findings extends beyond mere academic discourse. They hold practical implications for curriculum development, pedagogical strategies, and the provision of support services aimed at fostering a more inclusive and equitable technological environment within distance education. By recognizing and addressing the varied technology adaption levels across academic programs, educators and policymakers can better cater to the diverse learning needs and preferences of students, ultimately enhancing the quality and effectiveness of DE programs.

Moreover, there is also a significant association between technology adaption and both current level ($p = .000$) and study centre. This implies that the level of study (e.g., undergraduate vs. graduate) and the study centre where students are enrolled significantly influence technology adaption behaviours. Further investigation may be required to explore why these associations exist and how they can inform educational strategies. The findings are in line with Khalil et al. (2020); (Lazar, Panisoara, & Panisoara, 2020); Klein et al. (2021); Yu (2021) who stated that higher-level undergraduates displayed greater adaptability compared to their freshman and sophomore counterparts.

The study also revealed the significance of the study centre on students’ technology adaption. These findings highlight the influence of study centre environments on students’ technology adaption in distance education. The mean technology adaption scores serve as valuable indicators of students' technological proficiency within each centre. Higher mean scores, such as those observed in the HO and ACCRA WESLEY study centres, suggest a greater level of technological fluency among students in these environments. Conversely, lower mean scores, exemplified by the TAMALE BATCO study centre, highlight potential challenges and areas requiring improvement in technological adaption. By juxtaposing the collaborative efforts of the educational centre with the technological adaption levels of students across various study centres, we can infer that the centre's engagement in technology-related initiatives may contribute to fostering a more tech-savvy student body. However, further analysis is warranted to explore the specific factors driving variations in technology adaption scores among different study centres and to identify areas for improvement in promoting technological fluency across all educational settings. The significantly higher technology adaption scores in ACCRA WESLEY compared to ACCRA COLLEGE and ACCRA ST. JOHNS signify disparities even within the same geographical region. Conversely, the significantly lower scores in TAMALE BATCO highlight the need for focused efforts to bridge the technological gap and ensure equitable access to technological resources and support.

Drawing from this finding, we reject the null and accept the alternate. By recognizing and addressing the diverse technological needs and challenges across various study centres, educators and policymakers can design targeted interventions to promote technological fluency among students. These interventions may include enhancing infrastructure, providing specialized training and support, and implementing innovative instructional approaches tailored to the unique contexts of each study centre. By fostering a more inclusive and supportive technological ecosystem, stakeholders can empower students to harness the full potential of technology in their learning journey, ultimately advancing the goals of distance education.

Conclusion

The study examined how demographic factors influence technology adaption among distance education (DE) students in sub-Saharan Africa, focusing on age, gender, employment status, academic program, academic level, and study centre. Age significantly impacted adaption, with 60.5% of students aged 26-35 showing moderate adaption. Older students (36-45) had slightly higher scores, while the youngest (15-25) and oldest (46+) groups had lower scores. Gender differences were minimal, with males (57%) slightly outperforming females (43%), but not significantly. Employment status showed that employed students (77%) had higher scores, though the difference was not significant. Academic program was a crucial factor; Mathematics and English students had the highest adaption scores, while PGDE students had the lowest, indicating program structure and pedagogy influence adaption. The academic level also mattered, with higher-level students (level 400) adapting better than lower-level students (levels 100 and 200), suggesting that experience enhances proficiency. Significant differences were found among study centres, with Ho Technical University students having the highest adaption scores and Tamale Batco centre students the lowest, highlighting the role of resources and initiatives at study centres. Overall, while gender and employment status do not seem to be significant factors, variables such as age, programme, academic level, and study centre appear to influence technology adaption among DE students at the university.

Recommendations

- **Age and Experience:** While older students may have higher technology adaption scores, educators should tailor technological interventions to all age groups, considering individual experiences and attitudes towards technology.
- **Gender and Employment:** Since gender and employment status do not significantly impact technology adaption, interventions should be inclusive and focus on providing equal access to resources for all students.
- **Program-Specific Strategies:** Tailored strategies should be developed for different academic programs to address the specific needs and enhance technology adaption.
- **Academic Level:** Initiatives to increase technological fluency should start early in the academic journey, with continuous support as students progress.
- **Study Centres:** Investment in resources and technological infrastructure at study centres, especially those with lower adaption scores, is crucial to create an equitable learning environment.

Suggestion for Further Studies

- Further research is crucial to comprehend variations in technology adaption across study centres. Comparative studies investigating infrastructure, support, and instructional practices can reveal disparities. Qualitative research can capture students' and educators' perspectives on technology integration challenges and opportunities.
- Moreover, age-related differences, especially among mature students aged 36-45, warrant exploration

through longitudinal and qualitative studies.

- Additionally, understanding how different academic programs influence technology adaption patterns is essential. Comparative analyses and qualitative inquiries can inform discipline-specific integration strategies and support mechanisms in distance education.

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