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EXPLORING THE EFFECTIVENESS OF TECHNOLOGY INTEGRATION IN ELEMENTARY LEVEL OF EDUCATION IN DISTRICT ABBOTTABAD

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ABSTRACT
The purpose of this study is to determine how well District Abbottabad uses technology integration in elementary education. The purpose of the study is to evaluate the level of information and communication technology (ICT) integration in elementary school education and investigate how it affects a range of learning objectives, such as language acquisition, cognitive development, and problem-solving abilities. This study adds to our understanding of how technology can improve elementary school education by thoroughly examining technology integration techniques and how they affect students' learning. The results show a strong positive link between student learning outcomes and technology integration, underscoring the value of ICT integration in elementary education for improving language acquisition, cognitive development, and problem-solving abilities.
Key words: *cognitive development, ICT, language acquisition, problem-solving skills.*

INTRODUCTION

Today's students have grown up surrounded by technology (Egbert, 2009). Their daily activities, including learning, are closely linked to technology (Iivari & Ventä-Olkkonen, 2020). The impact of technology on education has been transformative. Costley (2014) argues that technology has a positive effect on student learning. Its importance in schools cannot be overstated, as it simplifies the process of teaching by educators and learning by students. Tinio (2002) further supports that information and communication technology (ICT) significantly influences the absorption of knowledge for both teachers and learners. According to Chang, Hsu, and Ciou (2017), it is widely recognized that future teachers need to be proficient in using ICT to effectively facilitate student learning. To meet this standard, preservice teachers are typically required to take ICT courses as part of their teacher preparation programs.

Globally, technology has made teaching and learning more enjoyable (Raja, 2020). Oblinger and Hawkins (2006) highlight the critical role of technology in online learning, with various tools being used to deliver knowledge effectively. The COVID-19 pandemic has further accelerated the adoption of online learning through digital tools like computers, laptops, and tablets (Kaharuddin, 2020).

International research consistently shows that effectively integrating technology enhances students' motivation, engagement, and interest in learning (Godzicki, Godzicki, Krofel & Michaels, 2013). Multimedia programs and online videos contribute to improved student motivation, engagement, grades, and achievements (Boster, Meyer, Roberto, & Inge, 2004; Maushak, Chen, & Lau, 2001). However, it's important to note that technology alone cannot boost student motivation; the key is how effectively teachers incorporate technology into their teaching methods (Lumley, 1991; Page, 2002).

In education, the use and integration of technology enrich the learning experience and help achieve educational goals with greater relevance and quality (Francis, 2017). Teachers' enthusiasm for using technology greatly influences their students' motivation and engagement in learning (Atkinson, 2000). There is evidence that the use of technology positively impacts student achievement and self-efficacy (Liu et al., 2006). However, technology must be used thoughtfully and intentionally to produce positive outcomes (Gramer & Smith, 2002). Research by Dawson (2012), Downes and Bishop (2012), and Martinez and Schilling (2010) has shown that student engagement and motivation increase when technology is used to create authentic learning experiences. The appeal of technology for students lies in its ability to connect their digital lives outside of school with their non-digital lives inside school.

Overall, understanding how to effectively integrate technology in education is crucial for creating engaging and impactful learning environments for students, but this requires careful and purposeful use to achieve the desired positive outcomes.

Research Problem

The goal of the research problem for the topic "Exploring the Effectiveness of Technology Integration in Elementary Level of Education" is to examine and evaluate how early childhood education settings' use of technology affects young learners' cognitive development, language acquisition, and problem-solving abilities. The goal of the project is to ascertain whether technology has a positive or negative impact on children's development during this crucial time of rapid brain growth and learning, as well as to investigate the possible advantages and difficulties of implementing technology in the classroom. In order to maximize technology's educational potential for young children, the research problem also attempts to create practical methods for integrating technology in ways that are developmentally and age-appropriate.

Significance of the study

Digital literacy and technological proficiency are critical abilities for future success in today's technologically advanced environment. Examining how well elementary school teachers integrate technology might help guarantee that young students are ready to use and understand it as they advance through the educational system and beyond. The creation and application of research-based teaching practices might result from an understanding of how well technology integration works in elementary education. Finding the best technological resources and methods can help young students learn more effectively and build their cognitive abilities as well as their problem-solving abilities. In order to support their children's early learning experiences, parents are essential. Parents can make well-informed decisions regarding the types of technology their children use by consulting research on the efficacy of technology integration.

OBJECTIVES OF THE STUDY

To find out integration of ICT in Elementary level education in District Abbottabad.

To examine the impact of technology integration on Elementary level learning outcomes, including cognitive development, language acquisition, and problem-solving skills.

LITERATURE REVIEW

Technology in Education

It is emphasized that using technology in the classroom can help students meet their learning objectives. In a study involving primary school pupils from disadvantaged socioeconomic backgrounds, it was discovered that classroom technology greatly enhanced students' sense of self and promoted greater classroom integration. The quotation from educational thinker John Dewey highlights how crucial it is to modify teaching strategies for today's pupils, who have grown up with technology and are digital natives (Bledsoe as cited in Pilgrim, 2012).

Use of technology in early education

In recent years, there has been a noticeable increase in the use of technology in early education. To improve teaching and learning, early childhood schools have incorporated technology such as computers, tablets, interactive whiteboards, educational apps, and multimedia materials (Haugland, 2012; Parette et al., 2019). These are a few of the most important applications of technology in early childhood education.

Interactive Learning Tools:
Interactive and captivating exercises that accommodate various learning styles are offered by educational applications and software intended for younger students. These resources can assist kids in developing critical basic abilities in a variety of topics, such as science, reading, numeracy, and the creative arts (Takeuchi & Stevens, 2011).

Digital Storytelling:
Technology allows for digital storytelling, where children can create and share their own stories using multimedia elements like images, sounds, and videos. This fosters creativity, imagination, and language development (Chiong & Shuler, 2010).

Online Resources:
To enhance classroom activities and provide extra learning materials, educators can access a multitude of online educational resources, including instructional websites, videos, and e-books (Plowman & Stephen, 2007).

Virtual Field Trips:
Through virtual reality (VR) or online platforms, early learners can "visit" different places, historical sites, and even explore outer space, enriching their understanding of the world around them (Chen & Chen, 2013).

Collaboration and Communication:
Technology facilitates communication and collaboration between teachers, parents, and students. Parents can stay informed about their child's progress and classroom activities through digital communication tools like emails and apps (Mantei & Kips, 2018).

Adaptive Learning:
Some educational software uses adaptive learning algorithms to tailor content based on a child's individual strengths and weaknesses, providing personalized learning experiences (Kleiman & Shah, 2017).

Early Coding and Robotics: Simple coding games and basic robotics kits introduce young children to the fundamentals of programming and problem-solving in a playful and age-appropriate manner (Bers, 2010).

Assessment & Progress Tracking:
Using digital quizzes, assessments, and performance tracking systems, technology can assist teachers monitor their students' progress and pinpoint areas that may require further attention (Herodotou et al., 2018).

Multilingual Learning: Early learners can discover and practice many languages using language learning applications and online programs, which foster multicultural awareness and communication abilities (Pan et al., 2019).

Learning management systems: These tools let instructors efficiently manage assignments, arrange and present material, and monitor the development of their students (Berge & Huang, 2004).
Even while there are many advantages to integrating technology into early education, screen time must be balanced with practical, hands-on learning opportunities. In order to encourage positive outcomes and outcomes that are developmentally appropriate, educators must also make sure that technology is utilized with intention and in ways that

METHODOLOGY
The purpose of this quantitative study is to examine how well technology integration works in primary school. A survey methodologies approach is used in the research, which includes quantitative data gathering and analytic approaches.

Research Design
In order to methodically monitor and characterize the effects of technology integration on elementary education, the study employs a descriptive research design.

Sample Selection
A random sampling technique is employed to select elementary schools that have implemented technology integration initiatives. The sample includes both urban and rural schools to ensure diversity in the study population.

Data Collection
Data is collected through surveys administered to gather insights into their perceptions of technology integration effectiveness. Additionally, academic performance data may be collected from school records.

Instrumentation
The survey instruments are designed based on established scales and validated measures of technology integration effectiveness, learning outcomes, and attitudes towards technology.

Data Analysis
Quantitative data analysis techniques, such as descriptive statistics, correlation analysis, and regression analysis, are employed to examine the relationships between technology integration and various outcome variables, such as academic achievement and student engagement.

RESULTS AND DISCUSSION

Table 1. *Descriptive Statistics for Usage of ICT skills at Elementary level of Education.*

Factors	SD	Means	Mode	Median
Learning Engagement	4.16578	21.5418	22.00	22.0000
ICT Skills	2.63170	19.1078	18.00	19.0000

Table 1 presents the usage of ICT (Information and Communication Technology) as independent variables, with data organized under two factors: Learning Engagement and ICT Skills. For Learning Engagement, the standard deviation (SD) is 4.16578, the mean is 21.5418, the mode is 22.00, and the median is 22.0000. In contrast, for ICT Skills, the standard deviation is 2.63170, the mean is 19.1078, the mode is 18.00, and the median is 19.0000. That participant demonstrate higher levels of Learning Engagement compared to ICT Skills

Factors	SD	Means	Mode	Median
Critical Thinking	3.05364	18.6170	21.00	19.0000
Language Acquisition	2.50563	15.6326	16.00	16.0000
Learning Creativity	2.46558	15.5603	16.00	16.0000
Problem Solving	2.50563	15.6326	16.00	16.0000
Academic Skill	2.28425	15.4638	16.00	16.0000

The mean score for critical thinking is 18.617, with a standard deviation of 3.05364. The mode and median are both 21.00 and 19.0000, respectively. This suggests that, on average, ICT has a moderately positive impact on critical thinking skills among participants, with most respondents scoring around the mode and median values. The mean score for language acquisition is 15.6326, with a standard deviation of 2.50563. The mode and median are both 16.00. This indicates that ICT usage has a positive impact on language acquisition, albeit slightly lower than the impact on critical thinking. However, the majority of respondents scored around the mode and median values. Participants reported a mean score of 15.5603 for learning creativity, with a standard deviation of 2.46558. Similar to language acquisition, the mode and median scores are both 16.00. This suggests that ICT contributes positively to learning creativity, with most respondents experiencing a moderate impact. The mean score for problem solving is 15.6326, with a standard deviation of 2.50563. The mode and median are both 16.00. This indicates that ICT usage positively influences problem-solving skills among participants, with a majority scoring around the mode and median values. Participants reported a mean score of 15.4638 for academic skill, with a standard deviation of 2.28425. The mode and median are both 16.00. This suggests that ICT has a positive impact on academic skill development, with most respondents experiencing improvement in this area.

Table 3 Correlation between the Overall the impact of technology integration on Elementary level learning.

LE	ICTS	CT	LA	LC	PS	AS
LE	1					
ICTS	.590**	1				
CT	.574**	.882**	1			
LA	.479**	.726**	.854**	1		
LC	.497**	.759**	.839**	.953**	1	
PS	.479**	.726**	.854**	1.000**	.953**	1
AS	.599**	.837**	.894**	.932**	.947**	.932** 1

**. Correlation is significant at the 0.01 level (2-tailed).

This variable shows a positive correlation with all other variables, ranging from 0.479 to 0.599, indicating that higher levels of learning efficiency are associated with higher levels of information communication skills, critical thinking, language acquisition, learning creativity, problem-solving, and academic skill. There is a positive correlation between information communication skills and all other variables, ranging from 0.590 to 0.837, suggesting that individuals with stronger information communication skills tend to exhibit higher levels of critical thinking, language acquisition, learning creativity, problem-solving, and academic skill. Critical thinking shows positive correlations with all other variables, ranging from 0.574 to 0.894. This indicates that individuals with stronger critical thinking abilities tend to have higher levels of language acquisition, learning creativity, problem-solving, and academic skill. Language acquisition demonstrates positive correlations with all other variables, ranging from 0.726 to 0.932. This suggests that individuals with better language acquisition skills tend to exhibit higher levels of learning creativity, problem-solving, and academic skill. Learning creativity exhibits positive correlations with all other variables, ranging from 0.759 to 0.947. This indicates that individuals with higher levels of learning creativity tend to have higher levels of problem-solving and academic skill. Problem-solving shows positive correlations with all other variables, ranging from 0.854 to 1.000. This suggests that individuals with stronger problem-solving abilities tend to exhibit higher levels of academic skill. Academic skill demonstrates positive correlations with all other variables, ranging from 0.932 to 1.000. This indicates that individuals with higher levels of academic skill tend to perform better in terms of learning efficiency, information communication skills, critical thinking, language acquisition, learning creativity, and problem-solving.

Table No.1 Model Summary for ICTS, LE

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.884[a]	.782	.782	1.42673

a. Predictors: (Constant), ICS, LE

The coefficient of determination (R) is 0.884, indicating that approximately 88.4% of the variance in the dependent variable is explained by the independent variables included in the model. The R square value (0.782) represents the proportion of variance in the dependent variable that is accounted for by the independent variables. In this model, approximately 78.2% of the variance in the dependent variable is explained by the independent variables. The adjusted R square value (0.782) takes into account the number of predictors in the model and adjusts the R square value accordingly. It provides a more conservative estimate of the proportion of variance explained. In this model, the adjusted R square value is the same as the R square value, indicating that the inclusion of predictors has not substantially affected the explanatory power of the model. The standard error of the estimate (1.42673) represents the average difference between the observed values of the dependent variable and the values predicted by the regression model. It provides a measure of the accuracy of the regression model in predicting the dependent variable.

Table No.2 ANOVA for ICTS and C

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	5135.630	2	2567.815	1261.476	.000[b]
	Residual	1428.966	702	2.036		
	Total	6564.596	704			

a. Dependent Variable: CT
b. Predictors: (Constant), ICTS, Len

The regression sum of squares (SSR) is 5135.630. The degrees of freedom for the regression model are 2, indicating the number of predictors in the model. The mean square for regression (MSR) is 2567.815, which is calculated by dividing the regression sum of squares by the degrees of freedom. The F-value is 1261.476, which is calculated by dividing the mean square for regression by the mean square for the residuals. The significance value (p-value) associated with the F-value is < .0001, indicating that the regression model is statistically significant. The residual sum of squares (SSE) is 1428.966. The degrees of freedom for the residuals are 702, calculated as the total number of observations minus the number of predictors in the model. The mean square for the residuals (MSE) is 2.036, which is calculated by dividing the residual sum of squares by the degrees of freedom for the residuals. The total sum of squares (SST) is 6564.596, representing the total variability in the dependent variable. The total degrees of freedom is 704, which is the sum of the degrees of freedom for the regression and residuals.

Table No. 3 Linear relationship ICTS and CT

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-1.160	.398		-2.910	.004
	Len	.060	.016	.082	3.745	.000
	ICS	.967	.025	.834	38.221	.000

a. Dependent Variable: CT

The unstandardized coefficient (B) for Learning Efficiency is .060, with a standard error of .016. The standardized coefficient (Beta) is .082. This suggests that for every one-unit increase in Learning Efficiency, the predicted outcome variable increases by .060 units, controlling for other variables in the model. The t-value of 3.745 indicates that the coefficient is statistically significant at p < .001. The unstandardized coefficient (B) for Information Communication Skills is .967, with a standard error of .025. The standardized coefficient (Beta) is .834. This indicates that for every one-unit increase in Information Communication Skills, the predicted outcome variable increases by .967 units, controlling for other variables in the model. The t-value of 38.221 indicates that the coefficient is highly statistically significant at p < .001. both Learning Efficiency and Information Communication Skills have statistically significant effects on the outcome variable in the regression model. Higher levels of Learning Efficiency and Information

Communication Skills are associated with higher values of the outcome variable.

Table No.4 Model Summary for ICS and LE

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.729[a]	.531	.530	1.71755

Predictors: (Constant), ICS, LE

The coefficient of determination (R) is .729, indicating that approximately 72.9% of the variance in the dependent variable is explained by the independent variables included in the model. The R square value (.531) represents the proportion of variance in the dependent variable that is accounted for by the independent variables. In this model, approximately 53.1% of the variance in the dependent variable is explained by the independent variables. The adjusted R square value (.530) takes into account the number of predictors in the model and adjusts the R square value accordingly. It provides a more conservative estimate of the proportion of variance explained. In this model, the adjusted R square value is very close to the R square value, indicating that the inclusion of predictors has not substantially affected the explanatory power of the model. The standard error of the estimate (1.71755) represents the average difference between the observed values of the dependent variable and the values predicted by the regression model. It provides a measure of the accuracy of the regression model in predicting the dependent variable.

Table No.5 Linear regression relationship ICTS and LA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	2348.969	2	1174.484	398.134	.000[b]
	Residual	2070.881	702	2.950		
	Total	4419.850	704			

a. Dependent Variable: LA

b. Predictors: (Constant), ICS, Len

The table presents the results of a linear regression analysis examining the relationship between ICTS and LA. The model indicates that there is a statistically significant relationship between the predictors and the dependent variable.Specifically, the regression model accounts for a substantial portion of the variability in LA scores, as indicated by the high F-value (398.134) and the associated significance level (p < .000). This suggests that the predictors, ICS and LEn, collectively contribute significantly to the prediction of LA. The coefficients of determination (R-squared) would further illuminate the proportion of variance in LA explained by the predictors. Unfortunately, these values are not provided in the table.

Table No. 6 Linear relationship LEn and ICS

a

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	2.248	.480		4.685	.000
	LEn	.046	.019	.077	2.406	.016
	ICS	.648	.030	.681	21.274	.000

a. Dependent Variable: LA

Table No. 6 displays the outcomes of a linear regression analysis exploring the relationship between LEn and ICS, both serving as predictors for the dependent variable LA. The analysis reveals that both LEn and ICS have significant effects on LA scores. LEn demonstrates a positive relationship with LA, with a standardized coefficient (Beta) of .077 and a corresponding t-value of 2.406, indicating statistical significance at p = .016. On the other hand, ICS exhibits a much stronger positive association with LA, evidenced by a Beta coefficient of .681 and a high t-value of 21.274, indicating strong statistical significance (p < .000)

Table No.7 Model Summary for ICS and Len

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.761[a]	.580	.579	1.60047

Predictors: (Constant), ICS, Len

Table No.7 provides a summary of the model's performance in predicting the relationship between ICS and LE.The coefficient of determination (R-squared) is .580, indicating that approximately 58% of the variability in the dependent variable can be accounted for by the predictors (ICS and LE) in the model. The adjusted R-squared, which considers the number of predictors and the sample size, is .579, suggesting a robust fit of the model. The standard error of the estimate, measuring the average discrepancy between the observed and predicted values of the dependent variable, is approximately 1.60047.

Table No.8 Linear regression relationship LC , ICS and LEn

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	2481.510	2	1240.755	484.385	.000[b]
	Residual	1798.178	702	2.562		
	Total	4279.688	704			

a. Dependent Variable: LC
b. Predictors: (Constant), ICS, Len

Table No.8 illustrates the outcomes of a linear regression analysis investigating the relationship among LC, ICS, and LEn. The model reveals a statistically significant relationship between the predictors and the dependent variable LC. This is indicated by the high F-value of 484.385 and its associated significance level (p < .000). The regression model explains a substantial proportion of the variability in LC scores, as evidenced by the large sum of squares for regression (2481.510) compared to the sum of squares for the residual (1798.178). Both ICS and LEn contribute significantly to the prediction of LC, as indicated by the predictors' inclusion in the model and their respective coefficients. However, the specific magnitudes of their contributions cannot be discerned solely from this table.

Table No. 9 *Linear relationship LC , ICS and LEn*

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1.808	.447		4.045	.000
	Len	.044	.018	.075	2.473	.014
	ICS	.670	.028	.715	23.585	.000

a. Dependent Variable: LC

Table No. 9 presents the results of a linear regression analysis examining the relationship between LC, ICS, and LEn.The analysis indicates significant effects of both ICS and LEn on the dependent variable LC. LEn demonstrates a positive association with LC, with a standardized coefficient (Beta) of .075 and a corresponding t-value of 2.473, indicating statistical significance at p = .014. Similarly, ICS shows a notably stronger positive relationship with LC, as evidenced by a Beta coefficient of .715 and a high t-value of 23.585, indicating strong statistical significance (p < .000).Moreover, the constant term is also significant (p < .000), with a value of 1.808

Table No.10 Model Summary for ICS and Len

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.729[a]	.531	.530	1.71755

a. Predictors: (Constant), ICS, LEn

Table No. 10 provides a summary of the model's performance in predicting the relationship between ICS and LEn.The coefficient of determination (R-squared) is .531, indicating that approximately 53.1% of the variability in the dependent variable can be accounted for by the predictors (ICS and LEn) in the model. The adjusted R-squared, which considers the number of predictors and the sample size, is .530, suggesting a reliable fit of the model. The standard error of the estimate, measuring the average discrepancy between the observed and predicted values of the dependent variable, is approximately 1.71755.Overall; the model demonstrates a moderate to strong explanatory power, indicating that both ICS and LEn are effective predictors of the dependent variable.

Table No.11 Linear regression relationship PS , ICS and LEn

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	2348.969	2	1174.484	398.134	.000[b]
	Residual	2070.881	702	2.950		
	Total	4419.850	704			

a. Dependent Variable: PS
b. Predictors: (Constant), ICS, Len

Table No. 11 presents the results of a linear regression analysis examining the relationship between PS, ICS, and LEn. The analysis indicates a statistically significant relationship between the predictors and the dependent variable PS, with a high F-value of 398.134 and a corresponding significance level of p < .000. The regression model explains a substantial proportion of the variability in PS scores, as evidenced by the large sum of squares for regression (2348.969) compared to the sum of squares for the residual (2070.881). Both ICS and LEn contribute significantly to the prediction of PS, as indicated by their inclusion in the model as predictors. However, the specific magnitudes of their contributions cannot be determined solely from this table.

Table No.12 Linear relationship LC , ICS and LEn

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	2.248	.480		4.685	.000
	LEn	.046	.019	.077	2.406	.016
	ICS	.648	.030	.681	21.274	.000

a. Dependent Variable: PS

The analysis reveals significant effects of both ICS and LEn on the dependent variable PS. LEn demonstrates a positive association with PS, with a standardized coefficient (Beta) of 0.077 and a corresponding t-value of 2.406, indicating statistical significance at p = 0.016. Similarly, ICS shows a notably stronger positive relationship with PS, as evidenced by a Beta coefficient of 0.681 and a high t-value of 21.274, indicating strong statistical significance (p < 0.000). Moreover, the constant term also holds significance (p < 0.000), with a value of 2.248.

Table No.13 Model Summary for ICS and LEn

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.847[a]	.717	.716	1.21691

a. Predictors: (Constant), ICS, Len

Table No. 13 provides a summary of the model's performance in predicting the relationship between ICS and LEn. The coefficient of determination (R-squared) is 0.717, indicating that approximately 71.7% of the variability in the dependent variable can be explained by the predictors (ICS and LEn) in the model. The adjusted R-squared, which considers the number of predictors and the sample size, is 0.716, suggesting a robust fit of the model. The standard error of the estimate, measuring the average discrepancy between the observed and predicted values of the dependent variable, is approximately 1.21691.

Table No.14 Linear regression relationship LC , ICS and LEn

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	2633.763	2	1316.882	889.268	.000[b]
	Residual	1039.564	702	1.481		
	Total	3673.328	704			

a. Dependent Variable: AS
b. Predictors: (Constant), ICS, LEn

Table No. 14 displays the results of a linear regression analysis examining the relationship between LC, ICS, and LEn with the dependent variable AS. The analysis indicates a highly significant relationship between the predictors and the dependent variable, as evidenced by the large F-value of 889.268 and its associated significance level of p < .000. The regression model explains a substantial proportion of the variability in AS scores, as indicated by the large sum of squares for regression (2633.763) compared to the sum of squares for the residual (1039.564).Both ICS and LEn significantly contribute to the prediction of AS, as indicated by their inclusion in the model as predictors.

Table No.15 Linear regression relationship , ICS ,Len and AS

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1.261	.340		3.711	.000
	LEn	.089	.014	.162	6.497	.000
	ICS	.643	.022	.741	29.800	.000

a. Dependent Variable: AS

Table No. 15 presents the results of a linear regression analysis examining the relationship between AS, ICS, and LEn. The analysis reveals significant effects of both ICS and LEn on the dependent variable AS.LEn demonstrates a positive association with AS, with a standardized coefficient (Beta) of 0.162 and a corresponding t-value of 6.497, indicating statistical significance at p =

0.000.Similarly, ICS shows a notably stronger positive relationship with AS, as evidenced by a Beta coefficient of 0.741 and a high t-value of 29.800, indicating strong statistical significance ($p < 0.000$). Moreover, the constant term also holds significance ($p < 0.000$), with a value of 1.261.

Discussions

The results from the series of linear regression analyses shed light on the relationships between various predictors (such as ICS and LEn) and different dependent variables (e.g., LA, PS, LC, AS). These findings are instrumental in understanding the influences of these predictors on the respective dependent variables.

In Table No. 7, the model summary for ICS and LEn shows a moderate to strong explanatory power, with approximately 53.1% of the variability in the dependent variable accounted for by the predictors. This suggests that both ICS and LEn are effective in predicting the dependent variable.

Moving to Tables No. 11, 12, and 13, which explore the linear relationships between LC, ICS, and LEn, the results consistently demonstrate significant effects of both ICS and LEn on the dependent variable PS. ICS appears to exert a notably stronger influence compared to LEn across these analyses. Additionally, the model in Table No. 13 indicates a robust fit, with a high coefficient of determination and adjusted R-squared values, suggesting that the predictors (ICS and LEn) provide a strong explanation for the variability in the dependent variable.

Table No. 14 further strengthens these findings by illustrating a significant linear relationship between LC, ICS, and LEn with the dependent variable AS. The high F-value and significant coefficients underscore the importance of both ICS and LEn in predicting AS.

Lastly, Table No. 15 corroborates the previous findings, showing significant effects of ICS and LEn on AS. ICS again demonstrates a stronger influence compared to LEn, indicating its crucial role as a predictor of AS.

Overall, these results suggest that both ICS and LEn are influential predictors across various dependent variables. However, ICS consistently emerges as the stronger predictor, highlighting its significance in explaining the variability in the dependent variables studied. These findings can inform decision-making processes and interventions aimed at enhancing outcomes related to the dependent variables under consideration.

Conclusions

Firstly, both ICS and LEn exhibit significant effects on the dependent variables across the analyses conducted. However, ICS consistently demonstrates a stronger influence compared to LEn.

Secondly, the models generally display a robust fit, as evidenced by high coefficients of determination and adjusted R-squared values. This suggests that the predictors (ICS and LEn) effectively explain a substantial portion of the variability in the dependent variables.

Thirdly, the findings underscore the importance of ICS as a significant predictor across various dependent variables, indicating its pivotal role in predicting outcomes such as LA, PS, LC, and AS.

Overall, the study highlights the significance of both ICS and LEn in explaining the variability in the dependent variables studied. These findings have implications for decision-making processes and interventions aimed at improving outcomes related to the dependent variables under consideration. Future research could further explore the mechanisms underlying these relationships and investigate additional predictors to enhance our understanding of the factors influencing the outcomes studied.

Recommendations

Keeping the conclusions in view, following recommendations are given to improve the situation.

1. There is a necessity for a pedagogical shift to implement new teacher education programs effectively.
2. Training in technological pedagogy should be provided in multiple phases.
3. Tutors in open and distance learning should be equipped with skills to utilize content with suitable technology for classroom practice.

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