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Technology Affinity, Interaction, Accessibility, Attitude to Learning, and Learning Performance: Examining the Interrelationships

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Abstract

There is unanimity among educational researchers regarding the causal effects of the use of technologies in education. However, issues concerning how human-technology attributes such as technology affinity, interaction, channel affinity and accessibility are related to learning remain unclear. This study examined how the levels of students' technology affinity, interaction, and accessibility are related to the students' attitudes to learning and learning performance. The study deployed the basic descriptive survey design. Five hundred and thirty-four students drawn from six Open and Distance Learning (ODL) universities located in three of the six States in South West, Nigeria participated. Data sources included four questionnaires and a 15-item Technology-mediated Scientific Cognitive Abilities Test. Data were analysed using descriptive statistics, correlation analysis and regression analysis. The study found that technology affinity levels exhibited a statistically significant but negative relationship with attitude to learning (β = -0.21, t = -3.69, p = 0.0000), while the relationship with learning performance was statistically non-significant but positive (β = -0.21, t = -3.69, p = 0.692). Interaction levels exhibited a non-significant and positive relationship with attitude to learning (β = 0.05, t = 0.99, p = 0.322), and a statistically non-significant but negative relationship with learning performance (β = -0.10, t = -1.40, p = 0.161). Accessibility was significantly but negatively related to attitude to learning (β = -0.13, t = -2.242, p = 0.025, intercept = -0.88) while exhibiting a non-significant but positive relationship with learning performance (β = 0.05, t = 0.68, p = 0.499, intercept = 0.25). The study concluded that significant relationships existed among and between the ODL students' technology attributes, attitude to learning and learning performance. It was recommended, among other things, that in adopting digital technologies for educational purposes, higher education institutions (HEIs) should sufficiently factor in the impact of the students' technology attributes.

Keywords: Technology affinity, interaction, accessibility, attitude to learning, learning performance.

1. Introduction

The increasing diffusion of digital technologies into societal life has implications for education and training as educational content is being transferred to the online realms at an increasing pace. Aside from impacting the way information and data are shared, stored and retrieved, this scenario is also diversifying the affordances of modern communications. Students can now attend virtual classrooms and take part in discussion forums in the comfort of their homes (Nieuwoudt, 2018). We are also confronted with the stark realities of what Mills *et al.* (2013) described as the "technology pervasive information environments of the 21st century" (p. 593), characterised by the

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growing capability of social networking technologies that empower students not only to get 'socially interactive' but also to assemble a learning community in the context of the online space (Bozkurt et al, 2017).

The consequence of these scenarios, in recent times, has been steady increases in empirical investigations regarding the causal effects of digital technologies on learning. However, given large-scale mixed causal evidence and methodological concerns about extant studies regarding the effects of technological objects on learning, the focus of research is gradually shifting towards discreet examinations of how learning develops rather than what new learning has been acquired through empirical and iterative investigations of technology attributes such as technology affinity, interaction, engagement, communication competence, interactivity, accessibility, channel affinity and so on. These human-technology attributes have been found to influence a new media user's performance, satisfaction, perceived mental effort and interest (Hietajarvi *et al*., 2019) as well as exert an impact on different dimensions of learning outcome (Bergdahl *et al*., 2018; Mills *et al*., 2013).

The aim of the present study, therefore, was to examine the interrelationships among technology affinity, interaction, accessibility, attitude to learning and learning performance with a specific focus on ICT concepts.

1.1 Technology Affinity and Learning Outcomes

Technology affinity is a unique technology attribute that defines the levels of a new technology user's physical association with the devices/tools of the new technologies. Johari (2016) described technology affinity as the "measurement for the level of engagement with technology devices in learning session" (p. 532). From a vantage point that equates affinity with an attitude, Edison and Geissler (2003) defined a similar construct – affinity for technology – as a "positive effect towards technology" (p. 140).

In this context, technology affinity simply represents the identity dimension of technology tools and devices, with affinity levels ranging from high to low levels. Affinity, though, is always positive, being essentially the opposite of aversion (Jordan, 2010). A high affinity, for example, will always propel the student media user to see a particular media or technology as possessing the inherent potential for meeting the needs of use as well as providing the gratifications expected and sought.

The amount of research currently devoted to the construct of technology affinity vis-à-vis its impact on cognitive outcomes remains sparse. Some studies, for example, Johari (2016), have investigated the relationships between technology affinity and information behaviour with the technology of higher institution learners based on gender. Several studies have, however, focused on related strands of affinity such as social media affinity (Gerlich *et al*., 2010), Internet affinity (Mansuri, 2014) and channel affinity (Sun *et al*., 2011).

1.2 Interaction and Learning Outcomes

Interaction is a broad phenomenon that reflects various shades of engagement. It has been described as comprising student-student, student-teacher and student-content interaction (Nieuwoudt, 2018). A measure of involvement or engagement with specific psychological objects is crucial to defining and understanding an interaction. With this perspective, the notion of interaction is defined and used within the conceptualization of this study as a synonym of learner-technology interaction or the concept of interaction involvement. Interaction involvement is the kind of engagement that has been defined as "a phenomenon that manifests in the interaction that takes place between the student and the subject" (Bergdahl *et al*., 2018, p. 101), the subject

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being, in the context of this study, the new technologies that the students interact with for learning and communication purposes. Chapman (2003), cited in Nieuwoudt (2018), described student engagement as comprising of 'motivated behaviour' that can be categorized based on the types of cognitive strategies students choose to utilize. Cegala (1981, p. 112), cited in Sun *et al*. (2011, p. 8), described the concept as "the extent to which an individual partakes in a social environment".

Research has established the existence of delicate links between engagement and interaction and various dimensions of learning outcomes. A handful of research findings such as Chen & Chen (2007) and Sher (2009) have linked high levels of interaction with positive effects on learning experience. Bergdahl *et al*. (2018) argued that given that engagement is vital for learning, students have the liberty to choose to engage with the learning material while the engagement itself may give rise to motivation for learning. The results of a study (Hietajarvi *et al*., 2019) have also demonstrated that students' use of digital tools to gain and share knowledge was related to higher study engagement.

1.3 Accessibility and Learning Outcomes

The construct of accessibility, in the context of this study, is inferred from and measured by an individual technology user's access to the new technologies. The indicators of this access include access to information, access to digital devices and access to online learning environments.

Research has examined the effects of technology access on the different dimensions of students' learning outcomes. The literature, however, reveals the existence of two diametrically opposed camps in this regard. On one side of the aisle is the camp of scholars such as Bergdahl *et al*. (2018) who denounced the disruptive and negative outcomes of access to technology in the context of the educational system. On the other side is the camp of researchers such as Bet *et al*., 2014 whose works generated a belief that buttresses the positive effects of technology access on learning outcomes. From the perspective of student engagement, Bergdahl *et al*. (2018) called attention to the challenge technology access poses for the student's ability to 'self-regulate'. Bet *et al*. (2014), in a study that involved 202 selected schools in Peru, found significantly positive effects of increased computer access on students' digital skills of about 0.3 standard deviations. Rashid and Asghar (2016) found, in another study, that access to and use of technology have no significant direct effect on academic performance.

2. Hypothesis

The present study examined the interrelationships between and among the levels of three human-technology attributes (technology affinity, interaction, and accessibility) and two clusters of learning outcomes (attitude to learning and learning performance) with a focus on ICT concepts. This was premised upon the fact that an examination of the extent to which a quantitative variable is a determinant or predictor of another variable is contiguous with an analysis of the modelling or relationships between the variables.

It was postulated that the highs and lows of the students' technology affinity, interaction, and accessibility could exert an influence on their attitude to learning and learning performance. The following hypothesis was, therefore, tested at a 0.05 level of significance:

HO_1: The technology affinity, interaction and accessibility of the open and distance learning students do not have any statistically significant relationship with their attitude to learning and learning performance.

3. Methodology

3.1 Research Design

This study was designed as a basic descriptive survey research.

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3.2 Sample and Sampling Techniques

The sample consisted of 534 students enrolled in open and distance learning (*ODL*) universities in the southwest region of Nigeria with sampling following a three-stage process. First, purposive random sampling was used to select three States (Lagos, Oyo and Osun States) from the six states in southwestern Nigeria based on the State having a full complement of both a National Open University of Nigeria (*NOUN*) Study Centre and a dual-mode conventional university's distance learning centre (*DLC*). Second, a stratified random sampling technique was used to select one *NOUN* Study Centre and one *DLC* from each of the three representative States to cap a total of six *ODL* institutions. Third, simple random sampling was employed to select students (n = 89) from each of the *ODL* Centres to cap the total number of students (n = 534) to whom the instruments were administered.

3.3 Research Instrument

The study's instruments comprised the following: 1) Technology Affinity Scale (*TAS*); 2) Interaction Involvement Scale (*IIS*); 3) Attitude to Learning Scale (*ALS*); 4) Technology Access Questionnaire (*TAQ*); and 5) Technology-mediated Scientific Cognitive Abilities Test (*T-SCAT*).

The *TAS*, *IIS*, and *ALS* scales were essentially multi-point formatted scales, consisting of Likert-type response options ranging from Strongly Agree, Agree, Undecided, Disagree, and Strongly Disagree graded 5, 4, 3, 2, and 1 respectively. The *TAQ* was patterned largely after the format prescribed in the EUROSTAT Model Questionnaire for a Community Survey on ICT Usage in Households and by Individuals (EUROSTAT, 2012). The scale incorporated a Yes-or-No response option with Yes and No graded 5 and 1 respectively and a Modified Likert-type response module with response options of Very Often, Often, Not Often, Not Very Often, and Never, which were graded 5, 4, 3, 2, and 1 respectively.

The T-SCAT, which measured learning performance, was essentially a 15-item objective multiple-choice question (*MCQ*) Cognitive Abilities or Aptitude Test developed by the researchers. The test items were graded by apportioning one (1) for each correct response and zero (0) for each incorrect response or unanswered question.

3.4 Procedure

All participants who consented to participate in the study were provided with advance information, following approval from their Centre Directors. This information included a description of the instruments to be administered, as well as assurances regarding the confidentiality and anonymity of their participation. Additionally, participants were informed of their right to withdraw their consent at any time after considering the provided information. They were also assured that there were no identified risks in participating in the research as the data collated from their responses would be exclusively used for the research project.

When administering the research instruments, the T-SCAT test was combined with the other four scales (TAS, IIS, ALS, and TAQ). Participants responded to these scales immediately after completing the T-SCAT questions. This sequential approach ensured accuracy and temporal contiguity in measuring students' technology attributes and learning outcomes. Although the T-SCAT and survey questionnaires were administered concurrently, each survey instrument and test measure were matched using a unique identification code. This coding ensured the validity of the correlation direction and strength between students' technology attributes and learning outcomes.

3.5 Analyses

3.5.1 Validity and Reliability

The instruments were validated through face- and content-validation by four experts in the educational foundations field. A pilot study was

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carried out at one of the universities in Lagos, Nigeria to assess the reliability of the instruments. The data from the test concerning the *TAS*, *IIS*, and *ALS* were analysed using Cronbach's Alpha, α, while the *TAQ* was based on the test-retest technique using the bivariate Pearson Correlation Coefficient analysis. The *T-SCAT* measure was analysed using the Kuder-Richardson Formula 20 (KR-20). The internal consistency reliabilities for the TAS, IIS, ALS, TAQ, and T-SCAT measures were found to be $\alpha = 0.79$, $\alpha = 0.75$, $\alpha = 0.79$, $r = 0.95$, and KR-20 = 0.75 respectively.

3.5.2 *Method of Data Analysis*

The research design compared two levels - Low and High - of three variables: Technology Affinity, Interaction, and Accessibility. The low versus high extremes of Technology Affinity (LT and HT), Interaction (LI and HI) and Accessibility (AL and AH) measures were determined based on the mean of the total scores for Technology Affinity ($M = 41.43$, $SD = 7.81$), Interaction ($M = 29.60$, $SD = 5.59$) and Accessibility ($M = 47.38$, $SD = 6.16$) respectively. Subjects with graded ratings that were below the mean of the total score in each case were partitioned as Low, while those whose graded ratings were above the mean of the total value were partitioned as High. For statistical analysis, the levels of technology affinity, interaction and accessibility were treated as dummy-variable regressors with a high level coded as 1 and a low level coded as 0.

The data analysis consisted of Descriptive Statistics, Correlation Analysis, and Regression Analysis, performed using SPSS version 25.0. Since the variables were previously confirmed to be normally distributed, parametric tests were applied to examine the data.

To test the hypothesis, two hierarchical multiple regression analyses were conducted with attitude to learning and learning performance separately regressed onto the three continuous predictors or covariates (technology affinity, interaction and accessibility), while averaging in the low-and-high dummy clusters of the predictor variables as categorical predictors or factors in steps. Given that there were two levels (low and high) in each case, one dummy variable was developed for each of technology affinity, interaction and accessibility to yield the following dummy variables used for statistical analysis: TA_Levels, II_Levels, and AC_Levels.

4. Results

4.1 Descriptive Data

The descriptive values for technology affinity, interaction, accessibility, attitude to learning, and learning performance are shown in Table 1. The values showed the coincidence or near coincidence of the mean, median and mode of the distribution of data relating to the individual variable, which suggested symmetric distribution. The values also revealed that data were normally distributed as skewness for technology affinity (-0.147), interaction (-0.262), accessibility (-0.355), attitude to learning (-0.213), and learning performance (-0.196) as well as kurtosis for technology affinity (-0.158), interaction (-0.385), accessibility (-0.242), attitude to learning (0.259) and learning performance (-0.262) were individually within the ±1 range.

The results of the correlation analysis conducted to identify the predictor variables that were significant correlates of the criterion variables are reported in Table 2. The results indicated that technology affinity was strongly and positively correlated with attitude to learning ($r_{(534)} = 0.56$, $\rho = 0.000$). There was also a weak but statistically significant positive correlation between technology affinity and learning performance ($r_{(534)} = 0.17$, $\rho = 0.000$).

Table 1: Descriptive Values for Technology Attribute and Learning Outcomes Variables

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Variable	Mean	Median	Mode	Std. Deviation	Skewness	Std. Error of Skewness	Kurtosis	Std. Error of Kurtosis
Technology Affinity	41.43	42.00	37.00	7.81	-0.147	0.106	-0.158	0.211
Interaction	29.60	30.00	30.00	5.59	-0.262	0.106	-0.385	0.211
Accessibility	47.38	48.50	49.00	6.16	-0.355	0.106	-0.242	0.211
Attitude to Learning	21.40	22.00	20.00	3.32	-0.213	0.106	0.259	0.211
Learning Performance	8.73	9.00	8.00	2.41	-0.196	0.106	-0.262	0.211
N = 534								

A strong, positive correlation between interaction and attitude to learning ($r_{(534)} = 0.61$, $\rho = 0.000$) and a weak, positive correlation between interaction and learning performance ($r_{(534)} = 0.10$, $\rho = 0.018$) were also revealed. The results also indicated a weak, positive correlation between accessibility and learning performance ($r_{(534)} = 0.27$, $\rho = 0.000$) and a moderate, positive correlation between accessibility and attitude to learning ($r_{(534)} = 0.31$, $\rho = 0.000$), which were statistically significant.

4.2 Test of Hypothesis

Table 3: Hierarchical Regression Analysis of Predictors of Attitude to Learning

Variables		1	2	3	4	5
1	Technology affinity	-	0.59** (p = 0.000)	0.47** (p = 0.000)	0.56** (p = 0.000)	0.17** (p = 0.000)
2	Interaction		-	0.36** (p = 0.000)	0.61** (p = 0.000)	0.10* (p = 0.018)
3	Accessibility			-	0.31** (p = 0.000)	0.27** (p = 0.000)
4	Attitude to learning				-	0.21** (p = 0.000)
5	Learning Performance					-

**Correlation is significant at the 0.01 level (2-tailed)
*Correlation is significant at the 0.05 level (2-tailed)

A summary of the results of the hierarchical regression analysis conducted for the prediction of attitude to learning is reported in Table 3. The overall model results indicated that Model 1($F(3, 530) = 135.46$, $p = 0.000$), Model 2 ($F(4, 529) = 107.42$, $p = 0.000$), and Model 3 ($F(6, 527) = 73.07$, $p = 0.000$) were statistically significant ($\rho < 0.001$). The analysis of step 1 inputs yielded an R-squared value ($R^2 = 0.43$, $\rho < 0.001$), indicates that technology affinity, interaction and accessibility scores accounted for 43.4% of the variance in attitude to learning ($F(3, 530) = 135.46$, $\rho < 0.001$). The introduction of Tech-Affinity Level scores in step 2 after controlling for technology affinity, interaction and accessibility caused an increase in R-squared value to 0.448 (i.e., 44.8% of the variance in attitude to learning accounted for by technology affinity, interaction, accessibility and Tech-Affinity level), yielding an R-squared Change value (0.014), which suggested that the addition of Tech-Affinity Level scores contributed 1.4% of additional variance in attitude to learning ($F(1, 529) = 13.62$), which was statistically significant ($p = 0.000$). In step 3, the

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inclusion of interaction levels and accessibility levels to the model caused

Table??

a marginal increase in R-squared value to 0.454 to account for an R-squared change value of 0.006, which could be interpreted that the addition of the two categorical predictors contributed a paltry 0.6% additional variance in attitude to learning, which was not statistically significant (F (2, 527) = 2.85, p = 0.059).

Model	R	R^2	Adjusted R^2	R^2 Change	B	β	SE	t	p
Step 1	0.66	0.43*	0.43*	-	-	-	-	-	-
Technology Affinity	-	-	-	-	0.12	0.28	0.02	6.36	0.000
Interaction	-	-	-	-	0.26	0.43	0.02	10.64	0.000
Accessibility	-	-	-	-	0.02	0.04	0.02	1.18	0.238
Step 2	0.67	0.45*	0.44*	0.01*	-	-	-	-	
Technology Affinity	-	-	-	-	0.19	0.46	0.03	7.03	0.000
Interaction	-	-	-	-	0.25	0.42	0.02	10.36	0.000
Accessibility	-	-	-	-	0.02	0.04	0.02	1.12	0.265
Tech-Affinity Levels	-	-	-	-	-1.38	-0.21	0.37	-3.69	0.000
Step 3	0.67	0.45**	0.45**	0.01**	-	-	-	-	
Technology Affinity	-	-	-	-	0.19	0.45	0.03	7.03	0.000
Interaction	-	-	-	-	0.23	0.38	0.03	6.66	0.000
Accessibility	-	-	-	-	0.08	0.14	0.03	2.46	0.014
Tech-Affinity Levels	-	-	-	-	-1.32	-0.20	0.38	-3.52	0.000
Interaction Levels	-	-	-	-	0.35	0.05	0.35	0.99	0.322
Accessibility Levels	-	-	-	-	-0.88	-0.13	0.39	-2.24	0.025

Statistical Significance: *ρ < 0.001; **ρ > 0.05

In terms of the contributions of both the continuous predictor and the categorical variables to the regression model, Table 3 shows that both technology affinity and interaction were significantly and positively related to attitude to learning in step 1, while accessibility exhibited a relatively weak, positive relationship, which was not statistically significant (p > 0.05). Tech-Affinity Level, which was added in step 2 of the model, was significantly but negatively related to attitude to learning (β = -0.21, t = -3.69, p = 0.000, intercept = -1.38), with the interpretation that for every one-unit increase in Tech-Affinity Level score, there would be a 1.38 decay in attitude to learning, suggesting that students falling in the high technology affinity range did not gain anything in terms of the affective dimension of learning. Of the two categorical predictor variables added in step 3 of the model, only accessibility levels exhibited a significant but negative relationship with attitude to learning (β = -0.13, t = -2.242, p = 0.025, intercept = -0.88). Interaction levels were, however, found not to be significantly related to attitude to learning (β = 0.05, t = 0.99, p = 0.322, intercept = 0.35).

A summary of the hierarchical regression results for the prediction of learning performance is reported in Table 4. The overall model results indicated that Model 1 (F (3, 530) = 14.48, p = 0.000), Model 2 (F (4, 529) = 10.88, p = 0.000), and Model 3 (F (6, 527) = 7.64, p = 0.000) were statistically significant (ρ < 0.001). The analysis yielded an R-squared value (R^2 = 0.08, ρ < 0.001), indicating that technology affinity, interaction and accessibility scores accounted for 8% of the variance in learning performance (F (3, 530) = 14.48, ρ < 0.001). The inclusion of Tech-Affinity Level scores in step 2 after controlling for technology affinity, interaction and accessibility did not affect the R-squared value,

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which maintained the 0.08 value, yielding a zero R-squared Change value (0.000). The interpretation for this is that the addition of Tech-Affinity Level scores contributed nothing to variance in learning performance ($F (1, 529) = 0.157$) in the model. The negligible change in F-value (F Change = 0.157) was also not statistically significant ($p = 0.692$).

In step 3, the addition of interaction levels and accessibility levels to the model caused a marginal increase in R-squared value from 0.076 to 0.080 to account for an R-squared change value of 0.004, which could be interpreted that the inclusion of the two categorical predictors contributed a paltry 0.4% additional variance in learning performance, which was not statistically significant ($F (2, 527) = 1.15$, $p = 0.318$).

In terms of the contributions of the continuous predictor variables and the categorical predictor variables to the regression model, Table 4 shows that both technology affinity and accessibility were weakly and positively related to learning performance in step 1, although the relationship between technology affinity and learning performance was not statistically significant ($\beta = 0.07$, $t = 1.20$, $p = 0.232$). Interaction exhibited a relatively weak, negative relationship, which was not statistically significant ($p > 0.05$).

This result pattern was sustained by the three variables in Step 2. Tech-Affinity Level, which was added in step 2 of the model, was weakly and negatively related to learning performance ($\beta = -0.21$, $t = -3.69$). The relationship was also not statistically significant ($p = 0.692$) with an intercept of 0.14, suggesting that the high and low levels of technology affinity exerted no impact on the cognitive dimensions of the students' learning outcomes.

The two categorical predictor variables (Interaction Levels and Accessibility Levels) added in step 3 of the model were not statistically significant. While interaction levels exhibited an insignificant and negative relationship with learning performance ($\beta = -0.10$, $t = -1.40$, $p = 0.161$, intercept = -0.46), accessibility levels exhibited a non-significant and positive relationship with learning performance ($\beta = 0.05$, $t = 0.68$, $p = 0.499$, intercept = 0.25).

The implication is that while the high and low levels of interaction contributed negatively to learning performance, the contribution of a high level of accessibility was statistically insignificant with the possibility of an impact at the 0.25 level.

Table 4: Hierarchical Regression Analysis of Predictors of Learning Performance

Model	R	R^2	Adjusted R^2	R^2 Change	B	β	SE	t	p
Step 1	0.28	0.08*	0.07*	-	-	-	-	-	-
Technology Affinity	-	-	-	-	0.02	0.07	0.02	1.20	0.232
Interaction	-	-	-	-	-0.01	-0.03	0.02	-0.48	0.630
Accessibility	-	-	-	-	0.10	0.25	0.02	5.20	0.000
Step 2	0.28	0.08**	0.07**	0.00**	-	-	-	-	-
Technology Affinity	-	-	-	-	0.03	0.09	0.03	1.09	0.276
Interaction	-	-	-	-	-0.01	-0.03	0.02	-0.52	0.605
Accessibility	-	-	-	-	0.10	0.25	0.02	5.19	0.000
Tech-Affinity Levels	-	-	-	-	-0.14	-0.03	0.35	-0.40	0.692

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Step 3	0.28	0.08**	0.07**	0.004**	-	-	-	-	-
Technology Affinity	-	-	-	-	0.03	0.09	0.03	1.04	0.298
Interaction	-	-	-	-	0.02	0.05	0.03	0.61	0.539
Accessibility	-	-	-	-	0.08	0.21	0.03	2.72	0.007
Tech-Affinity Levels	-	-	-	-	-0.12	-0.03	0.35	-0.35	0.726
Interaction Levels	-	-	-	-	-0.46	-0.10	0.33	-1.40	0.161
Accessibility Levels	-	-	-	-	0.25	0.05	0.37	0.68	0.499

Statistical Significance: *ρ < 0.001; **ρ > 0.05

5. Discussion

The present study examined the interrelationships within and among technology affinity, interaction, accessibility, attitude to learning and learning performance. The heterogeneity of the results of the hierarchical regression analyses conducted about the relationships within and among the low-and-high levels of the predictor variables vis-à-vis each of the two clusters of learning outcomes examined corroborates the findings of past studies, for example, Rashid and Asghar (2016), regarding the existence of distinct non-homogeneity about the impacts of technology attributes on different dimensions of learning outcomes. For instance, the high and low levels of technology affinity exhibited statistically significant but negative relationship to attitude to learning ($\beta = -0.21$, $t = -3.69$, $p = 0.000$, intercept = -1.38) but were weakly and negatively related to learning performance ($\beta = -0.21$, $t = -3.69$, $p = 0.692$, intercept = 0.14).

In the same vein, only accessibility levels exhibited a significant but negative relationship with attitude to learning ($\beta = -0.13$, $t = -2.242$, $p = 0.025$, intercept = -0.88), while the high and low levels of interaction were not significantly related to attitude to learning ($\beta = 0.05$, $t = 0.99$, $p = 0.322$, intercept = 0.35). However, while Accessibility levels exhibited a non-significant but positive relationship with learning performance ($\beta = 0.05$, $t = 0.68$, $p = 0.499$, intercept = 0.25), Interaction Levels exhibited an insignificant and negative relationship with learning performance ($\beta = -0.10$, $t = -1.40$, $p = 0.161$, intercept = -0.46).

Regarding access to technology, accessibility levels (high and low) were significantly but negatively related to attitude to learning, suggesting that high levels of accessibility are related to lower attitude to learning. The finding in

respect of the statistically non-significant but positive relationship between the high and low levels of accessibility and learning performance is congruent with Bet *et al.*'s (2014) finding that increased technology access exerts little or no impact on performances in Mathematics and languages. However, the finding is inconsistent with Al-Hariri and Al-Hattami's (2016) results in respect of a statistically significant and positive relationship between accessibility and learning performance. The implication of the results regarding beta weights and intercepts of ($\beta = -0.13$, intercept = -0.88) and ($\beta = 0.05$, intercept = 0.25) for attitude to learning and learning performance respectively to the high and low levels of accessibility might be that the contributions of the two extremes of accessibility towards predicting the students' learning outcomes are more significant for cognitive outcomes than effective outcomes. This corroborates Lee *et al.*'s (2013) study, which found that technology access

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enhances cognitive learning more than affective learning.

Regarding the low and high levels of technology affinity, the levels were found to be significantly but negatively related to attitude to learning (β = -0.21, t = -3.69, p = 0.000) and insignificantly and negatively related to learning performance (β = -0.21, t = -3.69, p = 0.692) in contrast to Gandema and Brown's (2012) findings. With a weak and negative beta weight, this means that while a high level of technology affinity occasions lower affective outcomes, both the high and low levels of technology affinity with an intercept (-0.14) exerted no positive impact on the student's cognitive outcomes.

Interaction levels were found not to be significantly related to attitude to learning (β = 0.05, t = 0.99, p = 0.322), while exhibiting a non-significant and negative relationship with learning performance (β = -0.10, t = -1.40, p = 161), meaning that both the high and low levels of interaction exerted no positive impacts on the student's learning outcomes. This corroborates Nieuwoudt's (2018) findings but contradicts Demir Kaymak and Horzum's (2013) findings that an increase in interaction drives an increase in the probability of students being able to fulfil their individual learning needs.
Overall, the results of the hierarchical regression analyses can be interpreted to mean that although the predictor variables are somewhat related to and can exert impacts on the outcome variables in different manners, their extremes or levels are not actual determinants of the depths and dimensions of learning outcomes.

These findings raise serious concerns about the influence of the semiotic resources of digital technologies and factors inherent in and characteristics of individual learners on the prediction of *ODL* students' affective and cognitive learning outcomes. They also challenge widely held assumptions regarding the pedagogical and educational effects of the pervasiveness of the new technologies.

6. Limitations and Recommendations for Future Studies

A primary limitation to the generalization of the results of this study is the delimitation of the study's sample to students of single-mode and dual-mode open-distance learning universities in the southwest of Nigeria. Although a more liberal approach to sample selection might have provided a more robust basis for generalization, the coverage of distance learning centres in conventional universities may provide a basis for the potential generalizability of the findings. Further studies may, therefore, consider examining the complex interrelationships between the constructs of both conventional- and ODL-university settings.

One other challenge is that, given the largely correlational nature of the study, it is practically impossible to infer causal relationships. Thus, real effects could very well not be what the results are reflecting and the effects of confounders may not be discoverable. Future research with an experimental design orientation is needed to examine causality as well as explore extraneous and other factors that may be exerting influences on learning outcomes and learners' cognitive capacity in the context of specific technology-mediated learning environments.

7. Conclusion

An increasing number of studies are targeting the exploration of how the complex interplays between and among certain technology attributes and the affective, cognitive and physical dimensions of learning are impacting decisions regarding the adoption of digital technologies as pedagogical and educational tools.

The hierarchical regression analyses conducted to investigate the effects of the high and low levels of the three predictor variables showed that while

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both technology affinity level and accessibility level were significantly but negatively related to the students' affective outcomes, interaction level was not significantly related to the affective outcomes of the students. In addition, while technology affinity level and interaction level were found to be insignificantly and negatively related to the student's cognitive outcomes, accessibility level was found to be insignificantly but positively related to the cognitive outcomes of the students.

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