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# IMPACT OF TECHNOLOGY ATTRIBUTES ON OPEN AND DISTANCE LEARNING STUDENTS' ATTITUDE TO LEARNING AND LEARNING PERFORMANCE

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Technology attributes, technology affinity, performance.

***Abstract***

This study was, therefore, aimed at investigating the impact of three key attributes of human-technology interactivities (technology affinity, interaction and accessibility) on ODL students' attitude to learning and learning performance. Cross-sectional-mixed-methods survey design was used for the study. Eight hundred and forty students drawn from six ODL Centres located in southwestern Nigeria participated. Four researcher-designed questionnaires and a 15-item Technology-mediated Scientific Cognitive Abilities Test (T-SCAT) were used to collect data. A sample (n = 48) of students, randomly selected from the representative sample, was also interviewed. Content analysis was used to analyse the study's qualitative data. Quantitative data were analysed using bivariate correlation analysis, descriptive statistics, and regression analysis. Results indicated statistically significant positive relationships between technology affinity and attitude to learning ($r_{(534)} = 0.56$, $p<0.01$), technology affinity and learning performance ($r_{(534)} = 0.17$, $p<0.01$), interaction and attitude to learning ($r_{(534)} = 0.61$, $p = 0.000$), interaction and learning performance ($r_{(534)} = 0.102$, $p = 0.018$), accessibility and attitude to learning ($r_{(534)} = 0.33$, $p = 0.000$) and accessibility and learning performance ($r_{(534)} = 0.27$, $p = 0.000$). Accessibility was not a significant predictor of attitude to learning but was found to be a significant predictor of learning performance ($\beta = 0.25$, $t = 5.20$, $\rho < 0.001$). The study recommended, amongst others, that higher educational institutions should adopt research-based approaches to align students' technology attributes with learning and the semiotic resources of technology.

## Introduction

The tremendous growth of the Internet beginning in the early 1980's is expanding the horizons of digitalisation revolution and bolstering the variety and capability of digital technologies. Bergdahl et al. (2020) ascribed to digitalisation the ability to mediate active participation in society at large, in private life and in education. This ability, though, is in spite of Osunwusi's (2020) argument that digitalisation processes are, paradoxically, hampering the realisation of the sustainable development goals as a result of inequalities within and among nations with respect to access to digital technologies.

The capability of digitalisation to mediate active participation as advanced by Bergdahl et al. (2020) not only underscores the pervading influence of the new technologies on humankind but also underpins, as Lezhnina and Kismihok (2020) pointed out, the crucial importance of human interaction with technology in the contemporary world. A direct consequence in the context of the educational realm has been the desire to understand how this ‘active participation’ factor - which Bergdahl et al. (2020) equated with students’ behavioural engagement in the course of a learning activity - reflects on a wide array of variables including quality of life, cognitive outcomes and a number of technology attributes that define the use of the new technologies for educationally related activities.

Technology attributes reflect unique characteristics that are a consequence of individuals’ engagements and interactivities with digital technologies. They are unique characteristics that are peculiar to individual learners and media users. These characteristics can influence a new media user’s performance, satisfaction, perceived mental effort and interest (Nicholson et al., 2008) and may have an impact on the learning process (Kozma, 1991, cited in Nicholson et al., 2008). Access to digital technologies, though, does not clearly presume degree of familiarity with the technologies (Kitmitto et al., 2018), but familiarity can drive engagement, which Bergdahl et al. (2018) have found to be vital for learning.

The increasing diffusion of digital technologies into societal life has, in recent times, been driving in-depth investigations into a wide variety of technology attributes – such as learner-technology interaction (also known as interaction involvement), technology affinity, channel affinity, interactivity, accessibility, media affinity, communication competence, interpersonal communication motivation, and so on – and the impacts they exert on the cognitive, behavioural, and emotional aspects of media users in the course of interactivities with digital technologies. Researchers such as Nicholson et al. (2008) and Weigel et al. (2010) have addressed issues surrounding the potential cognitive impact of the new technologies and of certain technology attributes on learning. Sun et al. (2011) also examined interaction involvement, channel affinity, and motivation for communication with a view to assessing their influence on channel use, while Cingel et al. (2014) investigated the role of access to and ownership of technology as predictors of social media use and online communication practices among adolescents.

Analysing, predicting, and understanding cognitive outcomes in the context of the use of digital technologies can be very challenging. Although earlier studies have explored issues revolving around the perceptions, attitudes, interaction and preferences of students regarding the use of social media and other tools of the new technologies such as an examination of the relationship between students’ beliefs and attitude toward social media use in education in relation to academic performance (Goel & Singh, 2016), student information behaviour for seeking and sharing information (Mills et al, 2013a), and an investigation of distance education students’ perceptions and preferences regarding use of social networking sites for communication and interaction purposes (Bozkurt et al, 2017), a review of the literature revealed that the explorations of the correlations among key technology attributes – which actually reflect factors inherent in the learners - and learning outcomes remain largely unclear and under-studied. Attributes such as: technology affinity, the “measurement for level of engagement with technology devices in learning session” (Johari, 2016, p. 532); learner-technology interaction or interaction involvement, which typifies behavioural engagement or student’s involvement in the course of a learning activity

(Bergdahl et al., 2020; Reeve, 2013) while encompassing involvement from both the cognitive and affective perspectives (Sun et al., 2011); and accessibility (which gauges the levels of an individual's ease of access to and frequency of use of the new technologies) have also received little attention.

In no sphere of the educational system, perhaps, has there been, since the dawn of the 21st century, a much livelier exhibition of the desire to innovate education using the new technologies than in the realm of Open and Distance Learning (ODL) along with its associated forms of education provision such as open-learning, distance education, e-learning, distance learning, and so on. Interestingly, the massive explosion of digital technologies has been identified as one of the elements underpinning the technological imperatives of lifelong learning (Osunwusi, 2020), which, in turn, represents an elixir for the ODL system. Given the widely acknowledged affinity of the educational realm in general and the ODL system in particular with technological innovations (Bozkurt et al., 2017; Henderson et al., 2017; Nieuwoudt, 2018; Okojie, 2013; Parusheva et al., 2018; UNESCO, 2002), it will be improper to conclude that key human-technology attributes that are specific to individual ODL students as a result of their interactivities with technologies for educationally related purposes would have any relationships with their learning outcomes and cognitive capacities.

**Purpose of the Study**

The purpose of this study was to examine the impact of technology attributes on the attitude to learning and learning performance of open and distance learning students. The specific objectives were to:

1) Examine the impact of the technology affinity levels of open and distance learning students on their attitude to learning and learning performance.
2) Examine the impact of the interaction levels of open and distance learning students on their attitude to learning and learning performance.
3) Examine the impact of the levels of accessibility of open and distance learning students to the new technologies on their attitude to learning and learning performance.
4) Investigate the individual and joint influence of the open and distance learning students' levels of technology affinity, interaction, and accessibility on their attitude to learning and learning performance.

**Research Questions**

1) What is the impact of the technological affinity levels of open and distance learning students on their attitude to learning and learning performance?

2) What is the impact of the interaction levels of open and distance learning students on their attitude to learning and learning performance?

3) What is the impact of the accessibility levels of open and distance learning students on their attitude to learning and learning performance?

4) What is the extent of the individual and composite influence of open and distance learning students' levels of technology affinity, interaction and accessibility on their attitude to learning and learning performance?

## Research Hypothesis

**HO$_1$**: The open and distance learning students' technology affinity levels do not exert any statistically significant impact on their attitude to learning and learning performance.

**HO$_2$**: The open and distance learning students' interaction levels do not exert any statistically significant impact on their attitude to learning and learning performance.

**HO$_3$**: The open and distance learning students' accessibility levels do not exert any statistically significant influence on their attitude to learning and learning performance.

**HO$_4$**: The technology affinity, interaction and accessibility levels of the open and distance learning students do not, either individually or cooperatively, influence any statistically significant changes in their attitude to learning and learning performance.

## Methodology

This study was designed as a cross-sectional survey research, deploying the concurrent triangulation design option of the mixed methods paradigm and incorporating the descriptive and analytical approaches to cross-sectional investigations. The study deployed two strands of investigation – a qualitative strand and a quantitative strand. The qualitative strand administered semi-structured interview questions on a representative sample of students (n = 48) randomly selected from the entire sample based on the selection criterion of eight students from each of the six representative ODL Centres. For the quantitative strand, the study's instrument comprised the following: A Technology-mediated Scientific Cognitive Abilities Test (T-SCAT), A Technology Affinity Scale (TAS), an Interaction Involvement Scale (IIS), an Attitude to Learning Scale (ALS), and a Technology Access Questionnaire (TAQ). The T-SCAT was an aptitude test developed to measure the students' learning performance based on performance on an objective multiple-choice questions (MCQ) test. It measured individual ODL student's cognitive abilities in terms of scientific knowledge and understanding acquired in relation to core digital technology concepts and the ability to apply those concepts to navigate the learning of science and solving scientific problems. The 15-item test was developed by the researchers based essentially on four subscales, namely: scientific reasoning and problem solving; numerical ability and image data analysis; identification and comprehension of digital scientific tools/techniques; and comprehension of technology-mediated quantitative relationships. The test items were graded by apportioning one (1) for each correct response and zero (0) for each incorrect response or unanswered question.
The TAS was developed essentially to measure the technology affinity of the students in relation to the use of digital technologies for communication and learning involving knowledge seeking, knowledge sharing and knowledge construction. The scale consisted of two modules. Module A (2A) comprised, for each of the static and dynamic technology clusters, a six-item questionnaire scored using a 5-point Likert-type measurement option, while Module B (2B) comprised a one-item open-ended question.The IIS scale was developed specifically to probe how learners interact with the tools and applications of the new technologies from the perspective of self-reported user-behaviour in relation to both the terrains of constructive and non-constructive communications. The scale consisted of two modules. Module A (3A) comprises an eight-item questionnaire scored

using a 5-point Likert-type measurement option, while Module B (3B) comprises a one-item open-ended question.

The ALS was used to assess learning outcomes from the perspective of the affective component of learning. It was a self-report scale that required students to make subjective assessments of their levels of learning from the affective standpoints. The ALS consisted of two modules. Module A (4A) comprises a six-item questionnaire scored using a 5-point Likert-type measurement option, while Module B (4B) comprises a one-item open-ended question. The TAQ measured the students' levels of accessibility to the tools and applications of the new technologies. The design of the instrument was patterned essentially 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 consisted of two modules. Module A (5A) integrated a Yes-or-No response option with Yes and No graded 5 and 1 respectively and a multiple choice response option, while Module B (5B) integrated a mix of multiple choice response and Yes-No question options, and a 5-point Modified Likert-type response options with responses of Very Often, Often, Not Often, Not Very Often, and Never, which were graded 5, 4, 3, 2, and 1 respectively.

The target population for this study consisted of students enrolled in the Study Centres of the single-mode National Open University of Nigeria (NOUN) and the Distance Learning Centres (DLCs) of dual-mode conventional universities located in the south west geo-political zone of Nigeria. A *source population* – providing the study's sample and consisting of ODL students located in three of the six States in the south west geo-political zone of Nigeria – was derived from the *target population*.

The sample consisted initially of subjects and participants (n = 840) drawn from the source population. The assembly of the sample and the determination of the sample size was premised upon the rule of thumb rather than on a sampling frame because of the difficulty inherent in obtaining an accurate sampling frame in this circumstance. In determining the sample, therefore, south-western Nigeria was partitioned into its constituent clusters of six States from which three States – Lagos, Oyo, and Osun – were selected using the purposive random sampling technique based on the State having a full complement of both a National Open University of Nigeria (NOUN) Study Centre and a dual-mode university's DLC.
Secondly, stratification by mode was used to partition the open and distance learning universities in the three States into two strata – the DLC stratum and the NOUN Study Centre stratum. The stratification yielded the random selection of one dual-mode DLC and one NOUN Study Centre from each of Lagos, Oyo and Osun States to cap at a total of six ODL Centres selected from the three representative States.

Thirdly, simple random sampling was employed to select participants (n = 140) from each of the ODL Centres to cap at a total number of participants (n = 840) on whom the instruments were planned to be administered. Of the 840 participants earmarked initially for participation, a total of 566 were actually accessed for instrument administration consequent, to a greater extent, upon the inherent characteristics of the ODL mode of learning delivery and the delimitation of the study's sampling units to subjects enrolled in science-specific disciplines. Thus, an actual sample (n = 566) and a final sample (n = 534), representing 67.38% and 63.57% response rates respectively, participated in the study. An analysis of the sample and sample participation is as shown in Table 1.

**Table 1: Analysis of the Study's Sample Distribution**

| ODL Identifier | Single-Mode Sector | | | | Dual-Mode Sector | | | | Total | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Initial Sample | Actual Sample | Cases Excluded (Missing Data) | Final Sample | Initial Sample | Actual Sample | Cases Excluded (Missing Data) | Final Sample | Initial | Actual | Case Exclusion | Final |
| **ODL 1 (Lagos)** | 140 | 120 | - | 120 | - | - | - | - | 140 | 120 | - | 120 |
| **ODL 2 (Lagos)** | - | - | - | - | 140 | 104 | 5 | 99 | 140 | 104 | 5 | 99 |
| **ODL 3 (Oyo)** | 140 | 77 | 6 | 71 | - | - | - | - | 140 | 77 | 6 | 71 |
| **ODL 4 (Oyo)** | - | - | - | - | 140 | 92 | 12 | 80 | 140 | 92 | 12 | 80 |
| **ODL 5 (Osun)** | 140 | 80 | 4 | 76 | - | - | - | - | 140 | 80 | 4 | 76 |
| **ODL 6 (Osun)** | - | - | - | - | 140 | 93 | 5 | 88 | 140 | 93 | 5 | 88 |
| **TOTAL** | **420** | **277** | **10** | **267** | **420** | **289** | **22** | **267** | **840** | **566** | **32** | **534** |

**LEGEND:**
**ODL1**: National Open University of Nigeria (Lagos).
**ODL2**: Distance Learning Institute, University of Lagos.
**ODL3**: National Open University of Nigeria (Ibadan Study Centre).
**ODL4**: Open and Distance Learning Centre, LAUTECH, Ogbomosho.
**ODL5**: National Open University of Nigeria (Osogbo).
**ODL6**: Obafemi Awolowo University Distance Learning Centre, Moro, Osun State.

*Reliability*

To determine their internal consistency reliabilities, the TAS, IIS, ALS, TAQ, and T-SCAT instruments were piloted at the University of Lagos on a sample of students ($n = 20$) in the case of TAS, IIS, ALS and TAQ and a sample of students ($n = 12$) in the case of the T-SCAT measure. The analysis of the TAS, IIS, and ALS datasets was based on the Cronbach's Alpha $\alpha$ while the reliability for the TAQ was computed using the bivariate Pearson Correlation Coefficient analysis. The T-SCAT datasets were analysed using the Kuder-Richardson Formula 20 (KR-20) statistical test, rather than the KR-21 based on the assumption that the items were not of equal or nearly equal difficulty.

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. These reliability coefficients were considered to be adequate. Nunnaly (1978), cited in Santos (1999), has indicated the value $\alpha = 0.7$ to be an acceptable reliability coefficient. Otuka (2004) cited Monnete et al. (1994) as acknowledging the fact that a correlation coefficient of 0.8 or more is necessary for affirming the reliability of an instrument. Fraenkel and Wallen (2008), as cited in Sabri (2013), also recommended the computation of a KR-20 reliability coefficient of 0.70 and above as an adequate value for confirming the reliability of a measure.

*Method of Data Analysis*

For the statistical analysis of quantitative data, the study deployed Descriptive Statistics, Correlation Analysis, and Regression Analysis. Parametric tests were used because variables were confirmed *a priori* to be normally distributed. All data were analysed using the Statistical Package for the Social Sciences version 25 (SPSS v.25.0).

A content analysis was conducted in the analysis of the qualitative data by quantitizing the qualitative data collected (Onwuegbuzie & Combs, 2011) through creating themes, categorizing and coding the identified themes, and taking a count of the frequency of occurrence of the respective categories and codes. The content analysis approach adopted was based on Levent and Keser's (2016) approach, which was patterned after Patton (2002) and premised upon an inductive approach that facilitates thematizing and categorizing the codes that emerge from responses to interviews and open-ended questions.

## Results

**Research Question 1:** *What is the impact of the technology affinity levels of open and distance learning students on their attitude to learning and learning performance?*

The descriptive values for the sample (n = 534) in relation to technology affinity, attitude to learning and learning performance are reported in Table 2. The results across the variables revealed, as can be seen in the table, variation in the variables' variance, which was clearly suggestive of the existence of relationships between and within the variables. The mean of the sample's technology affinity (M = 41.43, SD = 7.81), attitude to learning (M = 21.39, SD = 3.32), and learning performance (M = 8.73, SD = 2.41) also revealed wide variabilities that were consistent with the existence of varying degrees of associations between and within the variables.

**Table 2: Descriptive Statistics for Technology Affinity and Learning Outcomes Variables**

| Statistic | Technology Affinity | Attitude to Learning | Learning performance |
|---|---|---|---|
| N | 534 | 534 | 534 |
| Mean | 41.43 | 21.39 | 8.73 |
| SD | 7.81 | 3.32 | 2.41 |
| Minimum | 18.00 | 10.00 | 3.00 |
| Maximum | 60.00 | 30.00 | 14.00 |
| Variance | 61.03 | 11.04 | 5.80 |

**Research Question 2:** *What is the impact of the interaction levels of open and distance learning students on their attitude to learning and learning performance?*

**Table 3: Descriptive Values for Interaction and Learning Outcomes Variables**

| Statistic | Interaction | Attitude to Learning | Learning performance |
|---|---|---|---|
| **N** | 534 | 534 | 534 |
| **Mean** | 29.60 | 21.39 | 8.73 |
| **SD** | 5.59 | 3.32 | 2.41 |
| **Minimum** | 13.00 | 10.00 | 3.00 |
| **Maximum** | 41.00 | 30.00 | 14.00 |
| **Variance** | 31.21 | 11.04 | 5.80 |

The descriptive values for the sample (n = 534) in relation to interaction, attitude to learning and learning performance are reported in Table 3. The results across the variables revealed variation in the variables' variance, which strongly suggested the existence of relationships between and within the variables. The mean of the sample's interaction (M = 29.60, SD = 5.59), attitude to learning (M = 21.39, SD = 3.32), and learning performance (M = 8.73, SD = 2.41) also revealed wide variability consistent with the existence of varying degrees of associations between and within the variables.

**Research Question 3:** *What is the impact of the accessibility levels of open and distance learning students on their attitude to learning and learning performance?*

**Table 4: Descriptive Values for Accessibility and Learning Outcomes Variables**

| Statistic | Accessibility | Attitude to Learning | Learning performance |
|---|---|---|---|
| **N** | 534 | 534 | 534 |
| **Mean** | 47.38 | 21.39 | 8.73 |
| **SD** | 6.16 | 3.32 | 2.41 |
| **Minimum** | 29.00 | 10.00 | 3.00 |
| **Maximum** | 60.00 | 30.00 | 14.00 |
| **Variance** | 37.995 | 11.04 | 5.80 |

**Research Question 4:** *What is the extent of the individual and composite influence of open and distance learning students' levels of technology affinity, interaction and accessibility on their attitude to learning and learning performance?*

**Table 5: Descriptive Values for Technology Attribute and Learning Outcomes Variables**

| 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** | | | | | | | | |

The results 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 results 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. Values for skewness across the variables showed that the distribution was moderately left-skewed in each case. The normality of the distribution of data was also assumed from the histograms generated, each of which is approximately bell-shaped and showing symmetry about the mean.

**Hypothesis 1:** *The open and distance learning students' technology affinity levels do not exert any statistically significant impact on their attitude to learning and learning performance*.

A correlation analysis was conducted to test the following null hypothesis in respect of hypothesis 1:

$H_o: \rho = 0$,

where $\rho$ = population coefficient parameter.

The results of the correlation analysis (Pearson's r) as well as descriptive statistics on the means and standard deviations of the variables are presented in Table 6. The results indicated that technology affinity was strongly and positively correlated with attitude to learning ($r_{(534)} = 0.56$, $\rho<0.01$) while there was a weak but statistically significant positive correlation between technology affinity and learning performance ($r_{(534)} = 0.17$, $\rho<0.01$). The results also indicated a weak, positive correlation between attitude to learning and learning performance, which was statistically significant ($r_{(534)} = 0.21$, $\rho = 0.01$) due to the size of the study's sample (n = 534).

Overall, the results of the correlation analysis indicated that the p-value is less than the significance level, $\alpha = 0.05$, which led to the conclusion that the correlation was significantly different from zero (0) at $\alpha = 0.05$. Thus, the correlation was statistically significant, leading to the rejection of Hypothesis 1.

**Table 6: Pearson's r Correlations among Technology Affinity and Learning Outcomes**

| | Variables | 1 | 2 | 3 | M | SD |
|---|---|---|---|---|---|---|
| **1** | Technology Affinity | - | 0.56** | 0.17** | 41.43 | 7.81 |
| **2** | Attitude to Learning | | - | 0.21** | 21.39 | 3.32 |
| **3** | Learning Performance | | | - | 8.73 | 2.41 |

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

**Hypothesis 2:** *The open and distance learning students' interaction levels do not exert any statistically significant impact on their attitude to learning and learning performance*.

The results of the correlation analysis (Pearson's r) conducted to examine the statistical significance of the relationships between and within interaction, attitude to learning and learning performance are presented in Table 7. The results indicated that interaction was strongly and positively correlated with attitude to learning, $r_{(534)} = 0.61$, $\rho = 0.000$. The results also indicated a weak, positive correlation between interaction and learning performance, which was statistically significant at $\alpha = 0.05$ level ($r_{(534)} = 0.102$, $\rho = 0.018$). In terms of the association between attitude to learning and learning performance, the results indicated a weak, positive correlation between attitude to learning and learning performance, which was statistically significant ($r_{(534)} = 0.21$, $\rho = 0.000$) due to the size of the study's sample (n = 534). Overall, the results indicated that the p-value was less than the significance level, $\alpha = 0.05$, which led to the conclusion that the correlation was significantly different from zero (0) at $\alpha = 0.05$. Thus, the correlation was statistically significant, resulting in the rejection of Hypothesis 2.

**Table 7: Pearson's r Correlations between Interaction and Learning Outcome Clusters**

| | Variables | 1 | 2 | 3 | M | SD |
|---|---|---|---|---|---|---|
| **1** | Interaction | - | 0.61** | 0.102* | 29.60 | 5.59 |
| **2** | Attitude to Learning | | - | 0.21** | 21.39 | 3.32 |
| **3** | Learning Performance | | | - | 8.73 | 2.41 |

**Hypothesis 3:** *The open and distance learning students' accessibility levels do not exert any statistically significant influence on their attitude to learning and learning performance*.

The results of the correlation analysis (Pearson's r) conducted to examine the statistical significance of the relationships between and within accessibility and the two clusters of learning outcomes are summarised in Table 8.

**Table 8: Pearson's r Correlations between Accessibility and Learning Outcomes**

| | Variables | 1 | 2 | 3 | M | SD |
|---|---|---|---|---|---|---|
| **1** | Accessibility | - | 0.33** | 0.27** | 47.38 | 6.16 |
| **2** | Attitude to Learning | | - | 0.21** | 21.39 | 3.32 |
| **3** | Learning Performance | | | - | 8.73 | 2.41 |

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

The results revealed that accessibility was weakly but positively correlated with attitude to learning, $r_{(534)} = 0.33$, $\rho = 0.000$. There was also a weak but statistically significant positive correlation between accessibility and learning performance, $r_{(534)} = 0.27$, $\rho < 0.01$. The results also indicated a weak, positive correlation between attitude to learning and learning performance, which was statistically significant ($r_{(534)} = 0.25$, $\rho = 0.000$). Overall, the results indicated that the p-value was less than the significance level, $\alpha = 0.05$ (i.e., $\rho < 0.05$), which led to the conclusion that the correlation was significantly different from zero (0) at $\alpha = 0.05$. Thus, the correlation was statistically significant, leading to the rejection of the hypothesis.

**Hypothesis 4:** *The technology affinity, interaction and accessibility levels of the open and distance learning students do not, either individually or cooperatively, influence any statistically significant changes in their attitude to learning and learning performance*.

The Standard Multivariate Linear Regression Analysis was used to test the following null hypothesis in respect of Hypothesis 4:

$$H_0: \beta_1 = \beta_2 = \beta_3 = \ldots = 0.$$

To predict each of the two learning outcomes clusters from technology affinity, interaction and accessibility, two separate multivariate regression analyses were conducted. The results of the regression analyses are summarised in Table 9.

**Table 9: Results of Regression Analyses for the Prediction of Learning Outcomes from Technology Attribute Components**

| | Attitude to Learning (n = 534) | Learning Performance (n = 534) |
|---|---|---|

| Predictor Variables | β | t | p | β | t | p |
|---|---|---|---|---|---|---|
| Technology Affinity | 0.28 | 6.36 | 0.000 | 0.07 | 1.20 | 0.232 |
| Interaction | 0.43 | 10.64 | 0.000 | -0.03 | -0.48 | 0.630 |
| Accessibility | 0.04 | 1.18 | 0.238 | 0.25 | 5.20 | 0.000 |
| | $F = 135.46$, $p < 0.001$, $R^2 = 0.434$, Adjusted $R^2 = 0.431$ | | | $F = 14.48$, $p < 0.001$, $R^2 = 0.076$ Adjusted $R^2 = 0.071$ | | |

According to the results, technology affinity ($\beta = 0.28$, $t = 6.36$, $p < 0.001$) and interaction ($\beta = 0.43$, $t = 10.64$, $\rho < 0.001$) significantly predicted attitude to learning ($F(3, 530) = 135.46$, $\rho < 0.001$, $R^2 = 0.43$, Adjusted $R^2 = 0.43$), with the prediction explaining 43.4% of the total variance in attitude to learning. Accessibility was, however, found not to be a significant predictor ($\beta = 0.04$, $t = 1.18$, $\rho > 0.05$) of attitude to learning. With intercept values of 0.117 and 0.258, it can be said that for every one-unit increase in technology affinity ($\beta = 0.28$) and interaction ($\beta = 0.43$) scores, the students' attitude to learning values increased by 0.12 and 0.26 respectively. In relation to overall model fit, the R-squared value ($R^2 = 0.434$) as well as the similarity between the R-squared value and the Adjusted $R^2$ (0.431) suggested a good model fit.

Regarding the prediction of learning performance from technology affinity, interaction and accessibility, the results indicated that technology affinity ($\beta = 0.07$, $t = 1.20$, $p > 0.05$) and interaction ($\beta = -0.03$, $t = -0.48$, $\rho > 0.05$) were not significant predictors of learning performance ($F(3, 530) = 14.48$, $\rho < 0.001$, $R^2 = 0.08$, Adjusted $R^2 = 0.07$). Accessibility was, however, found to be a significant predictor ($\beta = 0.25$, $t = 5.20$, $\rho < 0.001$) that explained 7.6 % of the total variance in learning performance. In terms of overall model fit, the R-squared value ($R^2 = 0.076$) as well as the similarity between the R-squared value and the Adjusted $R^2$ (0.071) suggested a good model fit.

In relation to diagnostic tests to check collinearity and multicollinearity, collinearity statistics in respect of the regression analyses conducted indicated tolerance values of 0.57, 0.64, and 0.77 in relation technology affinity, interaction, and accessibility scores respectively. The VIF (Variance Inflation Factor) values for technology affinity, interaction, and accessibility were 1.76, 1.56, and 1.31 respectively. The fact that none of the tolerance values was below 0.10 and none of the VIF values was above 10 gave the indication that multicollinearity was not a problem.

*Qualitative Results*

For the analysis of the qualitative data, content analysis was performed on students' responses to both the open-ended survey and the semi-structured interview questions. One theme was identified from the framework of the questions relating to students' views on the consequential effects of technological objects on learning. Four categories reflecting the orientation of participant responses were generated and coded in respect of the theme.

The results of an analysis of the study's qualitative data in relation to students' responses on the quality and process of learning vis-à-vis digital technologies are tabulated in Table 10.

**Table 10: Analysis of Students' Views in respect of the Quality and Process of Learning**

| Theme | Categories | Codes | Participants (Single-mode) Frequency (F) | Participants (Dual-mode) Frequency (F) | Participants (Total) Frequency (F) |
|---|---|---|---|---|---|
| **Consequential effects on learning.** | *Influence of physical and behavioural engagements with technology on attitude to learning (affective dimensions).* | Positive<br>Negative | 38<br>26 | 36<br>27 | 74<br>53 |
| | *Influence of physical and behavioural engagements with technology on the quantum and quality of knowledge and understanding acquired (cognitive dimensions).* | Positive<br>Negative | 25<br>40 | 24<br>38 | 49<br>78 |
| | *Influence of access to and use of technology on attitude to learning (affective dimensions).* | Positive<br>Negative | 28<br>29 | 19<br>51 | 47<br>80 |
| | *Influence of access to and use of technology on the quantum and quality of knowledge and understanding acquired (cognitive dimensions).* | Positive<br>Negative | 29<br>21 | 48<br>28 | 77<br>49 |

As can be seen in Table 10, of the respondents who expressed their views regarding the influence of physical and behavioural engagements on the affective and cognitive dimensions of their learning experiences (F = 127), 74 reported positive influence on attitude to learning, 53 reported negative influence on attitude to learning, 49 reported positive influence on learning performance, and 78 reported negative influence on learning performance. Of the respondents who expressed their views on the influence of access to and use of technology on the affective and cognitive dimensions of their learning experiences, 47 reported positive influence on attitude to learning, 80 reported negative influence on attitude to learning, 77 reported positive influence on learning performance, and 49 reported negative influence on learning performance.

**Discussion**

The primary purpose of this study was to examine - through an exploration of interrelationships - the impact of technology attributes on ODL students' attitude to learning and learning performance. The study captured three key technology attributes – technology affinity, interaction, and accessibility. The aim was to transition beyond empirical examinations of the cause-effect of the adoption of digital technologies for teaching and learning by exploring the more germane questions of how attributes inherent in and characteristic of student technology users are related to the affective and cognitive dimensions of learning outcomes.

The findings regarding the relationships between individual technology attribute and each of the two clusters of the students' learning outcomes are not in line with the hypotheses ($HO_1$ to $HO_3$). The study found statistically significant positive relationships between technology affinity and attitude to learning, technology affinity and learning performance, interaction and attitude to learning, interaction and learning performance, accessibility and attitude to learning as well as accessibility and learning performance. These findings mean that an increase in any of the students' technological attributes would impact as well as drive proportionate increases in each of the affective and cognitive dimensions of the students' learning outcomes. An explanation for these relationship patterns can be tied to factors affecting the motivations, enthusiasm, and perceptions of the student's consequent upon the novelty surrounding technological affordances. An increase in interaction, for example, has been found to revolve around an increase of the probability of the students being able to fulfill their individual learning needs (Demir Kaymak & Horzum, 2013) based on the belief that interacting with technology will improve communication with peers and tutors (Vululleh, 2018). Research has also found a correlation between technology affinity and motivation that is strongly indicative of a level of enthusiasm that could drive improved cognitive outcomes (Albus et al., 2021).

The correlations between and within technology affinity, interaction and the two clusters of learning outcomes suggest that ODL students, particularly those with high levels of technology affinity and interaction, might be finding the autonomy and the multi-sensory learning affordances provided by the tools and applications of digital technologies to be an exciting way to upscale their cognitive and affective outcomes. The findings relating to statistically significant positive relationships between interaction (both constructive and non-constructive) and learning outcomes contradict Nieuwoudt's (2018) results but are in line with other studies, for example Wong (2013), demonstrating a possible relationship between students' engagement or interaction with online resources and the students' overall academic achievement. The finding that there was a statistically significant and positive relationship between accessibility and learning performance is consistent with Al-Hariri and Al-Hattami's (2016) results regarding the observation of a significant relationship between students' access to technology and their achievements in health colleges.

Concurrent with past studies that find a distinct non-homogeneity in relation to the relative impacts of technology attributes on different dimensions of learning outcomes (Nicholson et al, 2008;

Rashid & Asghar, 2016), the findings of this study revealed that the statistical significance of the effects of the predictor variables – technology affinity, interaction and accessibility – on each of the affective and cognitive dimensions of the students' learning outcomes varied significantly. For example, while technology affinity ($\beta = 0.28$, $t = 6.36$, $p < 0.001$) and interaction ($\beta = 0.43$, $t = 10.64$, $p < 0.001$) significantly predicted attitude to learning, the two variables were found not to be statistically significant predictors of learning performance in contradiction to Gandema and Brown's (2012) findings, which reveal the statistical prediction of academic performance by students' engagement or interaction. Thus, the effects of technology affinity and interaction towards the prediction of the students' learning outcomes were more meaningful for affective outcomes than for cognitive outcomes. The non-prediction of learning performance by technology affinity and interaction can be interpreted to mean that students of higher education institutions have not actually transitioned from mono-modal learning engagements to multi-modal digital learning engagements as corroborated by Henderson et al.'s (2017) study, which finds that digital technologies are neither transforming university teaching and learning nor disrupting the 'student experience'. An alternative explanation might be that the students had reduced affinity for digital technologies and were not, therefore, very disposed to learning with digital technologies particularly social media, which contrasts with Rashid and Asghar's (2016) results as well as Mills et al.'s (2013b) findings in respect of greater preference for learning with social media in the context of greater positive attitude towards school, lower preferences for immersive affinity for technology and higher self-reported creative tendencies. Interestingly, in this context, research has also found no significant differences in levels of technology affinity as a result of time spent on social media (Johari, 2016).

In line with the findings of the present study, accessibility was not a significant predictor ($\beta = 0.04$, $t = 1.18$, $p > 0.05$) of attitude to learning in agreement with the hypothesis, but was found to be a significant predictor ($\beta = 0.25$, $t = 5.20$, $p < 0.001$) of learning performance. Thus, regarding the effects or contributions of accessibility towards predicting the students' learning outcomes, the effect on cognitive outcomes is more meaningful than the effect on affective outcomes. This essentially corroborates the findings of Lee et al. (2013), which reveal that technology access enhances cognitive learning more than affective learning as well as Jacobsen and Forste's (2011) findings on the perspective that the use of electronic media among university students can engender both positive and negative consequences. The findings regarding the statistically significant prediction of learning performance by accessibility, however, contrasts sharply with the findings of other past studies (e.g., Rashid & Asghar, 2016). They also challenge the findings of other past studies (Chen & Peng, 2008; Kirschner & Karpinski, 2010; Rosen et al., 2013), which report the association of reduced academic performance with excessive access to and use of the internet and social media.

The implication of the findings on the contributions of each of the technology attributes towards predicting the students' learning outcomes is that while both technology affinity and interaction exhibited the potential of fostering positive attitude to learning, their contributions towards engendering meaningful cognitive outcomes were insignificant. In the same vein, while accessibility made no contribution to attitude to learning, it was an active enabler of meaningful cognitive outcomes, which Lee et al. (2013) have found to be particular to the domains of basic skills and factual learning. The non-prediction of affective outcome by accessibility buttresses the findings by Weigel et al. (2010) to the effect that students use the affordances of network access in the classroom less for the satisfaction of academic curiosity.

The heterogeneity characteristic of the relative impacts of technology attributes on learning outcomes as revealed by the regression analyses conducted in this study can be explained in a number of ways. Nicholson et al. (2008), for instance, have ascribed such variations to characteristics of the task being performed. Another explanation might be the characteristics of the semiotic resources of digital technologies, particularly factors that form an integral element of the design of technology-driven learning materials. These factors have actually been found to be related to the various semiotic resources that technology provides (Nouri, 2019) in different forms of learning environments, including the use of annotations in a virtual reality learning (Albus et al., 2021) and multimedia learning (Richter et al., 2016) environments.

The overall implication, therefore, is that in order to ensure significant relation in human-technology interaction vis-à-vis the various dimensions of learning the patterning of the semiotic resources and use of signaling are significant. This is more so because of the inadequacy of the support of e-learning in ensuring effective incentives for learning (Duong Van, 2016) outside critical user-enabled and technology-related factors. Research on the use of signaling in the form of textual annotations in a virtual reality learning has provided corroborating evidence that the use of signaling principle leads to improved learning outcomes particularly for learners with low prior knowledge (Richter et al., 2016), although such improvement is evident in recall rather than in comprehension or transfer questions (Albus et al., 2021). Factors that are allied to this might be user-system interface and interaction factors (Lin, 2009) as well as users' attitude and perception towards the various presentation styles of the semiotic resources of particular media. Notably, research has found an association between reduced grades and the technology users' experience arising from the affordances of technology specifically the experiences related to learning and obtaining information off the screen (Bergdahl et al., 2020).

An alternative explanation for these variations particularly with respect to affinity and user-technology engagements might be the extraneous and intrinsic factors surrounding usage patterns of individual technology users, specifically factors surrounding channel or application adoption and use, including behavioural intention, which Wang and Liu (2009) have found to have positive impacts on usage. Within this framework, past studies have found affinity to be a significant predictor of channel use, while interaction involvement has been found to be a non-significant predictor of hourly channel use (Sun et al., 2011).

The content analysis of the study's qualitative data underscores many of the findings that emerged from the statistical analyses of the study's quantitative data. Views regarding the influence of technology affinity and interaction on affective and cognitive outcomes corroborated the results of the regression analyses conducted to investigate the prediction of affective and cognitive outcomes by technology affinity and interaction. The same result patterns were recorded regarding views on the influence of accessibility on affective and cognitive outcomes. Influence of physical attachment and behavioural engagement on affective outcomes recorded 74 positive responses as against 53 negative responses, while the influence on cognitive outcomes garnered 49 positive responses as against 78 negative responses. Influence of accessibility on affective outcomes had

47 positive responses as against 80 negative responses, while the influence of accessibility on cognitive outcomes had 77 positive responses as against 49 negative responses.

Overall, the findings bolster the study's assumptions that statistical inferences and predictions concerning the associations within components of technology attributes and learning outcomes can illuminate the path towards strategies, theoretical pathways, procedures and processes for developing and adopting technology-driven pedagogies that can guarantee effective teaching and learning. Further studies can overcome the primary limitation to the generalization of the results of the present study by examining the complex interrelationships between technology attributes and learning outcomes in the context of a multiplicity of university settings. Future studies may also build upon the present study by investigating the moderating effects of particular semiotic resources of technology in the context of specific technology-mediated learning environments.

## Conclusion

The present study deployed the cross-sectional-mixed-methods research design to examine the interrelationships between the technology attributes and the learning outcomes of a sample of ODL students in the context of the use of digital technologies. The results of the study did not support all the hypotheses with the exception of hypothesis 4 ($H0_4$) in relation to the statistical prediction of attitude to learning by accessibility and the statistical prediction of learning performance by technology affinity and interaction.

The current research supports the premise that students' technology attributes have significant bearings not only on the students' learning outcomes but also on decisions surrounding the feasibility of adopting certain technologies and certain features and semiotic resources of specific technologies for the purpose of enhancing the educational and pedagogical effects of digital technologies. Based on the findings of this study, it is reasonable to conclude that educational institutions and governmental organizations responsible for regulating the media and digital technology spheres incur tremendous responsibilities in ensuring that the perspectives of technology use both by the students and the university faculties are factored into strategies for mainstreaming e-learning and e-administration.

The general conclusion, therefore, is that technology affinity, interaction and accessibility constitute an important element for evaluating the trajectories of learners' learning outcomes. A key deliverable that has emerged from the findings of this study in relation to the relative predictive weights of the technology attributes explored is that it is the contextual dimensions of the use of digital technologies for educationally relevant activities and not the actual digital technology objects that determine the trajectories of the pedagogical and educational benefits of digital technologies. This bolsters Osunwusi's (2019) argument that it is the educational context in which technology is used rather than technological infrastructure that drives policy frameworks for mainstreaming e-learning.

## Recommendations

Based on the findings of this study and the issues discussed as well as the conclusions made, the following recommendations are necessary:

1) Higher education institutions (HEIs), specifically ODL institutions, should assume greater responsibility for providing support for the broad variety of students' technological characteristics in the context of the educational use of digital technologies. This would involve taking due cognizance of several factors surrounding the characteristics. It would also exert a demand on the educational institutions to, as a matter of importance, adopt research-based approaches to developing and adopting digital learning resources that embed the contextual dimensions of technology use.
2) Educational institutions that are desirous of designing and implementing digitalized learning resources should take concrete steps towards ensuring the adequacy of digital balance with the incorporation of informational elements relating to possible students' behavioural intention and reactions towards specific semiotic resources of technology, particularly resources in respect of tools and applications that have demonstrated striking affinity for the educational realms.
3) A multi-sectorial involvement and multi-stakeholder partnerships are essential to upscaling technological characteristics.

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