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THE EFFECT OF COGNITIVE KNOWLEDGE ACQUIRED FROM INDUSTRIAL TRAINING ON COMPUTER SCIENCE DEGREE PROJECT

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ABSTRACT

Cognitive knowledge from Industrial training (IT) shapes the practical skills of graduate students. However, it is not clear how cognitive knowledge acquired in lower level courses impact the quality of degree project of students in final year.. Using the scores obtained from the IT course of 361 Computer Science students in a Nigerian University, cognitive knowledge content transfer and application are investigated. Results revealed a significant correlation of 0.23 at $p = 0.05$ and a slight knowledge transitional mean increase of 0.795 from their IT course to the B.Sc project. A total of 70.11% of the students who chose their degree project topic based on their IT experience performed better than their counterparts and demonstrated transitional cognitive knowledge application. An 86% accuracy was recorded in predicting the class of honours of students based on their IT courses. using K-Nearest Neighbour (KNN) machine learning algorithm.

Keywords: *Cognitive Knowledge, Industrial Training, Skill, Labour, Graduate Students, Intelligence*

1. INTRODUCTION

According to the author in [1], Cognitive knowledge is rational knowledge which is the source of scientific knowledge needed for technological development. Cognitive knowledge is essential for science education. Cognitive knowledge can also refer to intelligence abilities as mentioned in [2] which defines it as a person's ability to fit into an environment and improve on learning based on experience. In particular, cognitive knowledge can be associated with three basic abilities: creative, analytical, and practical abilities as mentioned in [3]. These abilities which are pertinent to science education ought to be properly directed in the course of training students in the field. One major means of shaping students to this end is through Industrial training (IT). There is no doubt that practical knowledge and training are a precursor to skilled labour and subsequent economic development. The author in [4] sees training as an integral part of vocational or career development. The authors in [5] encourage practical learning because it introduces new ideas through examples. Again, the author in [6], sees practical training as an opportunity to learn about a concept that had not been known while the authors in [7], see practical classes as a tool for enhancing students' motivation and knowledge extension in theories and concepts relating to their field.

Training should be organized and coordinated for cognitive knowledge to develop. A major educational scheme that provides prerequisite in-school training for higher education students is the Students' Industrial Work Experience Scheme (SIWES) otherwise known as Industrial Training (IT) scheme. This is a compulsory training programme introduced as part of the curriculum, especially in Nigerian higher schools. The scheme was introduced in Nigeria in 1974 to improve the skill as well as practical knowledge of tertiary students. Little wonder the Nigerian University Commission (NUC) approved SIWES as a required course for graduation. SIWES is usually assigned a course code with an associated unit load of 4. The course is usually done in the second semester of the penultimate year. During this period, the students apply to industries which are related to their field of study and specialization interest. These industries

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accept students for IT and on-the-job training experience. The training may endure for a period of 3 to 6 months pending the resumption of a new session. When the students return to the school, they are expected to submit their Log Book and a formal report of their experiences during the training. The Log Book contains the daily routine, observations, challenges and workings of the student during the training. It specifies the duties assigned to the student and how results were obtained. The Log Book is usually marked or inspected by an on-site supervisor within the industry or establishment where the training is done. When the students resume studies, they are required to present a seminar or verbally defend their experience during the training programme. It is upon this and the Logbook that a performance score is finally awarded.

Industrial training contributes to the quality of labour by improving expertise in the respective field of study. Industrial training tries to address the growing concern in the labour market which is that graduates of institutions of tertiary learning seem to lack adequate practical background foundation for employment in industries. This allegation has made some graduates unemployable. Hence, Industrial training schemes are designed to provide an opportunity for students to familiarize themselves with field equipment and machinery before they graduate. There are several benefits associated with Industrial training schemes. The author in [8] sees IT as a tool for bridging the gap between theoretical concepts and realities. The authors in [9] see it as a promoter of vocational studies, while the author in [10], emphasised the importance of Industrial training on graduate skill development. In the field of Agriculture, the benefits are seen in fish farming while in business education it is seen as being a tool for business education students to acquire the skill [11],[12]). In addition, there is convincing evidence that several students have gained employment through the training programme. Such students, on graduation, had gone back to the industries they did their IT and were found employable due to the earlier training received in the same industry.

In addition to all these, Industrial training courses are meant to be a preparatory course for the main project work of the student offered in the final year. The expectation at the end of every industrial training programme is that students translate the knowledge gained during the training into their B.Sc project course which is an extension of their industrial training. The B.Sc project is another industrial training course designed to allow the students to put into practice the entire practical experience acquired in the field. The B.Sc project course ensures that students apply the cognitive intelligence of industrial training to develop a self-made practical project. In Computer science, for instance, students are meant to acquire cognitive knowledge from SIWES in the areas of Programming, Networking, Web Design, Security, Computer maintenance and Engineering, Robotics, Computation and others. Hence, the B.Sc project course is a test of the level of expertise of a student as related to the field of study. It is expected of students to choose project topics within the confines of their experience during the IT programme. Hence both the SIWES and B.Sc project courses are seen as very serious courses for the students

Industrial Training is globally accepted and supported by governments of several countries as it is seen as a force that drives technological revolutions [13]. In Nigeria for instance, the government spends hugely on sustaining the programme [14],[15]. The same goes for the government of Turkey, the United States, Malaysia and the Korean government in [16],[17],[18] and [19] respectively. There are several challenges against IT programme prospects as seen in [20],[21] and [22]. However, due to the ensuing benefits, a lot of proposals and suggestions have been proffered towards improving Industrial Training programmes [23],[24],[25]. Hence, being that Industrial Training programmes have come to be regarded as a basic component of skill acquisition and learning in our higher schools, there is, therefore, a need to look at its effect on the overall performance of graduate students.

The heavy amount spent on IT programmes and the poor quality of degree project continues to raise questions on the justification of the programme. In recent times, it has been perceived that the standard of education is on the decline [26], [27]. This is because, most graduate students no longer meet the demands of the labour market as they lack the practical competency and expertise required for employment. The authors in [28] have attributed this dismal performance to a curricular that places less emphasis on practical training. However, it has been argued that the IT programmes are designed to equip students with the relevant industrial and practical knowledge and the state of the art industrial tools in their respective fields in line with the findings of [29]. At final year, students are expected to show some level of mastery of their field. In Computer science for instance, the IT programme is done at the

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penultimate level. During such training, students learn new skills required for the labour market. They learn things like Networking, Programming, Web design and others. It is therefore expected that students apply the cognitive knowledge gained during such training to improve their degree projects. The question therefore is to what extent do students actually do this and justify the attention, effort and heavy funds lavished in IT programmes.

On this basis, the purpose of this research is therefore to ascertain if students actually apply the cognitive knowledge gained from IT courses to their final degree project. The research will address specific objectives such as; (a) To ascertain the relationship between IT and degree project courses in higher education. One way of doing that is to look at the correlation between the SIWES scores and the project scores of the students. A priori expectation is that there shall be an increase in project scores for every SIWES score. This will indicate a positive relationship affirming that the knowledge acquired in SIWES is eventually applied to improve degree projects thus justifying the scheme. This investigation will be achieved using Pearson correlation, (b) to ascertain the percentage utilization of cognitive knowledge in the IT and degree courses. (c) to predict the class of honours a student may likely be awarded at the end of his/her degree programme based on performance in IT courses. The prediction will be carried out using the KNN (K-Nearest Neighbour) classification model. In doing so, two research questions will be addressed which are: (i) Is the relationship between the IT and degree courses offered in higher schools significant? (ii) To what extent do students utilize the cognitive knowledge acquired in the IT course to improve performance in the degree course? The paper is thus presented in the subsequent 7 sections including the literature review, the methodology, analysis, findings, implications as well as the conclusion. The significance of the work is to justify the continuity or not of government's heavy funding on the programme.

2. LITERATURE REVIEW

One may be interested to know if indeed industrial training has any effect on the cognitive knowledge of students' development in their respective fields. In doing so, we looked at the work of [30] on the effect of SIWES on the professional development of Library and Information Science. The descriptive research focused on the South-West part of Nigeria and tried to find out if truly the students of Library Information Science (LIS) had their IT training in the library as it should. They used questionnaires and analysed their data using descriptive statistics and simple percentages. Their findings reveal that most of the students were trained in libraries and that the training was positive according to the response from the students. They also discovered that challenges such as finance, inadequate supervision of trainees, irregular academic calendar and disruption of studies were some challenges of the scheme. However, the study did not base its findings on actual classroom results and the performance of students. Similarly, a review of SIWES as an IT course was done with a view of identifying the reasons behind the success and desired results [31]. The authors reviewed the performance of SIWES in four countries and used their findings to describe the effect of SIWES in Nigeria. The research yielded positive results in that regard but its approach was strictly qualitative and for comparison purposes. As such, the interpretations were not based on inferences obtained from valid analysis of quantitative data. However, the research substantiates the claim that indeed Industrial training schemes influence students positively in their respective fields of study.

On the same note, the authors in [32] tried to investigate the effectiveness of IT on Engineering students. Using a sample of 21 and 26 male and female students respectively, the impact of twelve weeks of IT was tested on three parameters namely; knowledge, skill and general attitude to IT training from the perspective of the students. Their findings reveal that half of the students showed cognitive knowledge and skill acquisition at the end of the programme.

Specifically, on cognitive skill acquisition, the author in [33] investigated the extent of skill demonstrated by students after an IT programme. They focused on four generic skills which are; communication skills, teamwork skills, critical thinking and problem-solving. The study reveals that IT training contributes to the development of generic skills among students. In addition, they demonstrated that students develop their generic skills in tune with their culture. This shows that cognitive knowledge could be shaped to individual advantage.

The work of the authors in [34] tried to improve the aim of IT programs and skill acquisition by bridging the gap between academics and industries. They proposed a cloud-based management and supervision approach to the SIWES programme. According to them, during the training, stakeholders such as industries and institutions could use the platform to monitor the daily activities of a student and as well assess students directly. In addition, through the platform, recommendations and suggestions could be made to improve the training of the student during the programme duration. The research was purely based on system design without emphasis on empirical data.

In the same vein, an effort to improve the efficiency of IT programmes that foster cognitive knowledge was made by [35]. In the research, a recommender system for suggesting the appropriate training industry for students based on previous knowledge was developed. Their model made use of the C4.5 algorithm which is a derivative of a decision tree to classify their data for prediction. A web application was subsequently developed based on the underlying models. However, their approach does not proffer solution to the problem at hand which is to measure the impact of IT on the students and how they apply it in their degree project.

Cognitive knowledge acquired from IT courses was used by [36] to predict the final performance of students. Using machine learning, a study of the historical grades of University Engineering students was done with a view of making predictions that will benefit the students. The decision tree algorithm was used to classify and study the behaviour and trend of students' grades for a period of 2016 to 2018 academic session. The research supports the impact of industrial training on higher education but focused on predicting students final performance and not on the impact of the training.

Most of the contributions on Industrial training seem to focus more on emphasizing the positive effect on industries, academic performance and ways of improving the programme without paying attention to how the latent cognitive knowledge acquired from IT impacts the students as they progress in their studies. There is, therefore, a need to look at the transition impact of IT courses to understand if the cognitive knowledge gained in it is applied in the subsequent courses.

3. METHODOLOGY

This research employs an empirical approach to investigation. Using descriptive and inferential statistics of graphs, correlation and T-test, information is obtained from the primary result data and a conclusion is drawn from that Finally, the KNN algorithm was employed to predict the possible class of honours of students based on previous performance.

3.1 Conceptual formulation

The Department of Computer Science offers two major IT courses; COS374 (Student Industrial Work Experience) and COS471 (Project) as 4 and 6-unit load courses respectively. These two courses are regarded as part of the practical courses in which students are assessed to ascertain the extent of their preparedness to go into the labour market. These two courses are taken seriously by the department due to the high unit load attached to them. When the students return from their Industrial training, they are scored through seminars, log books and written reports. This is a measure adopted by the department to ensure that the scores awarded are commensurate with students' efforts. The SIWES course (COS374) is usually seen as a prerequisite course before the main degree Project which is one in the final year (4th year). It is expected that students apply the cognitive knowledge acquired from the experience in the COS374 (SIWES) training programme to COS471 Project). To encourage this, students are allowed to choose a project topic from the context of what they learnt in COS374. Our interest in this, therefore, is to ascertain to what extent cognitive knowledge is utilized to improve the result of COS471.

The duration of the SIWES training is between 2-3 months. Within this period, students are absorbed in industries for training. Typical industries available for Computer science students to apply for SIWES training and the nature of skills acquired are presented in Table 1.

Table 1: Skill Acquisition Industries For Computer Science Students

S/No	Industry	Expected skill acquired
1.	Cyber Cafes	Networking, resource sharing, computer repairs
2.	Software developers	Web design, soft computing, game programming, robotics
3.	Administrative offices	Desktop publishing, graphic design, daily routine computation, accounting and scheduling
4.	Production industries	Expert system development, fuzzy logic control, artificial

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		intelligence
5.	Banking industries	Security control, Cloud Networking and maintenance
6.	Sales and Recycling industries	Hardware training, maintenance and repairs

Students' interests and areas of specialization are kindled based on the nature of the industry where they find themselves for the SIWES programme. For instance, those that served public Cyber cafes (public internet providers) are bound to learn the basics of computer networking and maintenance. They will be well acquainted with resource sharing from a practical perspective being that most of the Cafés make use of several computers sharing limited resources like printers, scanners and other input/output hardware devices necessary for their work. Subsequently, students who served under a such company will become confident in such areas and will naturally begin to develop a keen interest in it. The opportunity to actualize the interest provides itself in the B.Sc degree Project where students are expected to develop their working software or hardware based on all that they have learned during their stay in the tertiary institution. During this period, students are advised as well as encouraged to pick project topics relevant to their SIWES training experience. They, therefore, use this opportunity to perfect their training under the supervision of lecturers who specialize in such areas.

3.2 Data Collection

This research investigation is based on primary data collected on graduate students of Computer Science, at a Nigerian University and specifically on their IT courses (SIWES and B.Sc Project courses). The result data spans four (4) academic sessions which are; 2016/2017, 2017/2018, 2018/2019 and 2019/2020. The Grade Point Cumulative Average (CGPA) and the class of honours of the students were also extracted from both the departmental exams unit and the University portal[1]. The dataset is made up of 85 students from the 2016/2017 session, 71 from the 2017/2018 session, 92 from 2018/2019, 73 from the 2019/2020 session and 40 students from previous sessions who happened to have been cleared within the sessions under study. The scores from two (2) IT courses which are; COS374 and COS471 representing the SIWES and Degree Project scores were extracted for the research. In addition, those that picked their project topics in line with their SIWES experience were also earmarked. The two courses are compulsory requisites before graduation as such there were no missing data.

To employ the KNN predictive model, the required data were also extracted. The aim of employing the KNN model was to predict the possible class of honours of the students based on their performance in the two IT courses. Firstly, the CGPA of students using only the SIWES and Project scores were computed. Similarly, their CGPA (on other courses) without the two courses were also computed as SPC and OCC using equations 4 and 5 respectively. For the SPC, a new Total grade point (TGP_{SP}) was computed using the grades obtained from both SIWES and Project. The grade point and associated unit for the two courses (GP_S, GP_P) were then used to compute the combined total grade point which is then subtracted from the final grade point of the student (available as data). The SPC was thus obtained by dividing the TGP_{SP} by the combined total unit from the two courses ($Unit_S$, $Unit_P$).

The analysis data were thus extracted using the layout in Table 2.

Table 2: Data Layout

Reg.No	Col_1	Col_2	Col_3	Col_4

Key:
Col_1 = SIWES_Score
Col_2 = Project_Score
Col_3 = Other_Courses_CGPA
Col_4 = SIWES_Project_CGPA
Col_5 = Final_CGPA
Col_6 = Honours

3.3 Hypothesis testing

Two sets of hypotheses will be tested in this work.

(a) Correlation test

H_o: The correlation between the IT courses is zero.

(b) T-test

H_o: There is no significant difference between the two IT courses

3.4 Model specification

We present the definitions and specifications of the variables for the CGPA computation model.

3.4.1 Definitions

[1]Data source: (https://www.unn.edu.ng/

To facilitate the computation of requisite variables (not collected through data), we shall define them first as follows:

(a) SW_sc = SIWES scores from COS374
(b) PR_sc = Project scores from COS471
(c) Cum_CGPA = Cummulative CGPA obtained from other courses apart from SIWES and Project
(d) Final_CGPA = The actual CGPA of the student
(e) Hr = Class of honours awarded
(f) Dev = Deviation between the Final CGPA and Cumulative CGPA
(g) $R_{SW\_scPR\_sc}$ = Pearson correlation coefficient between SIWES and Project score
(h) d = the difference between SIWES score and Project score
(i) PDT = Percentage deviation in score trend from SIWES to Project
(j) SPC= SIWES_Project_CGPA
(k) OCC = Other_Courses_CGPA
(l) TGP = Total grade point of final CGPA
(m) TCE = Total credit earned from all courses
(n) GP_S = Grade point for SIWES
(o) GP_P = Grade point for Project
(p) TGP_{SP} = Total grade point for SIWES and Project
(q) TCE_{SP} = Total credit unit for SIWES and Project
(r) $Unit_S$ = SIWES unit load = 4
(s) $Unit_P$ = Project unit load = 6
(t) $Point_S$ = {0,1,2,3,4,5}: {F= 0, E = 1, D =2, C = 3, B = 4, A = 5}
(u) $Point_P$ = {0,1,2,3,4,5}: {F= 0, E = 1, D =2, C = 3, B = 4, A = 5}

3.4.2 Model formulation

To conduct the investigations, some variables were computed from the collected data to make up the requirements for the applied statistics.

The Pearson correlation coefficient between the SIWES and Project scores is computed using equation 1.

$$RSW\_scPR\_sc = \frac{\sum_{i=1}^{n}(SW_{sc}-\overline{SW_{sc}})(PR_{sc}-\overline{PR_{sc}})}{\sqrt{\sum_{i=1}^{n}(SW_{sc}-\overline{SW_{sc}})^2}\sqrt{\sum_{i=1}^{n}(PR_{sc}-\overline{PR_{sc}})^2}} \quad (1)$$

The paired T-test statistic for the work is given in equation 2

$$t = \frac{\sum_{i=1}^{n} d}{\sqrt{\frac{n(d^2)-(\sum d)^2}{n-1}}} \quad (2)$$

$$PDT = \frac{\sum_{i=1}^{n} count\_of\_Increase - \sum_{i=1}^{n} count\_of\_decrease}{\sum_{i=1}^{n} count\_of\_increase} \times 100 \quad (3)$$

$$GP_S = Unit_S \times Point \quad (4)$$

$$GP_P = Unit_P \times Point \quad (5)$$

$$TGP_{SP} = TGP - (GPs + GPp) \quad (6)$$

$$TCE_{SP} = Unit_S + Unit_P \quad (7)$$

$$SPC = \frac{TGP_{SP}}{TCE_{SP}} \quad (8)$$

$$OCC = \frac{(TGP-TGP_{SP})}{(TCE-T\quad_{SP})} \quad (9)$$

To compute the OCC, the TGP_{SP} and the TCE_{SP} are removed from the students CGPA and computed without the SIWES and Project points and units. At the end, the combined CGPA of SIWES and Project was computed. Similarly, the Cumulative CGPA from other courses was equally computed.

The algorithm for computing the projected SIWES and Project CGPA (SPC) is given as follows:

```
For (i=1; i<=n; i++)
{
TGPS = 0
TGPp = 0
get_the PointS from {0,1,2,3,4,5}, where {F=0, E=1, D=2, C=3, B=4, A=5}
get_the PointP from {0,1,2,3,4,5}, where {F=0, E=1, D=2, C=3, B=4, A=5}
for (i=1; i<=number_of_courses; i++){
#Compute GPS
GPS = UnitS * PointS
#Compute GPP
GPP = UnitP * PointP
TGPS = TGPS + GPS
TGPp = TGPp + GPp
}
Get_the TGP (from data)
TGPSP = TGP – (TGPS + TGPP)
TCESP = Sum_of (UnitS + UnitP)
SPC= TGPSP/TCESP
}
```

3.4.3 The K-Nearest Neighbour Classification Model

The K-NN algorithm is a machine learning model which uses a supervised learning approach to predict for instance a path to a destination where

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the destination is known. K-NN algorithm's simple working principle is to store all available cases and classify new cases by a majority vote of its k neighbours. The K-NN algorithm classifies data points to a given category using a training set. In other words, the K-NN captures information on all training cases and classifies any new cases based on similarity. Predictions are made for a new instance (x) by searching through the entire training set for the K most similar cases (neighbours) and summarizing the output variable for those K cases.
The equation for the K-th minimum distance using the Euclidean distance is given as:

$$d(x,y) = \sqrt{\sum_{i=1}^{m}(x_1 - y_1)^2} \qquad (10)$$

The algorithmic steps of the KNN algorithm are summarised as follows:

a. *Determine the parameter K which is the number of nearest neighbours*
b. *Calculate the distance between the query instance and all the training samples*
c. *Sort the distance and determine the nearest neighbours based on the kth minimum distance*
d. *Gather the categories of the neatest neighbours*
e. *Use the simple majority of the category of nearest neighbours as the prediction value of the query instance.*

The overall impact of SIWES and the Project on the final performance of the students was modelled using the predictive KNN machine learning algorithm. The performance of the students depends to an extent on their SIWES and project scores, hence, it is, therefore, necessary to model the performance based on these variables as well as the cumulative performance obtained in the other courses (SIWES and Project not included). This way, a student can predict his/her final class of honours at the end of the programme if the student sets a target for himself/herself on what to score in SIWES and Project to meet the desired goal. Hence, if a student knows his cumulative score from all other courses, he can predict his final performance through the SIWES and Project scores.

The KNN model made use of three independent variables and one dependent variable. The independent variables are; SIWES score, Project score and Cummulative CGPA from other courses while the dependent variable is the class of honours to be awarded. The class of honours to be classified include First Class, Second Class (Upper), Second Class (Lower), Third Class and Pass. Thus using the previous academic records of students who have finished especially their SIWES, Project, Cumulative performance and class of honours, the KNN algorithm was used to classify and predict the class of honours of students.
The model was designed to use 75% of the data as train data while the remaining 25% was used as test data. The computation was done in python (Pycharm environment). The data was standardized and the KNN model was fit into it. To determine the most suitable *k* (number of nearest neighbours to be considered) for optimal prediction performance, an error curve for the train and test data was plotted. The curve showed that *k* = 3 was a suitable value. Hence the model was computed for *k* = 3 neighbours. The confusion matrix (matrix of true and false predictions) was also plotted to test the accuracy of the model.

4. ANALYSIS

To test for the correlation between the SIWES and Project scores, two columns of data representing SIWES and Project scores (the IT courses) were used. Firstly, a scatter plot was done to visualize the data trend as shown in Figure 1.

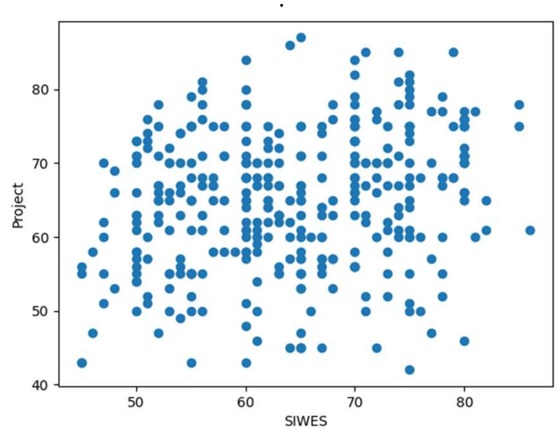

Fig. 1: Scatter Plot Of SIWES And Project Scores

The plot suggests a linear relationship between the SIWES and Project scores. However, a confirmatory correlation test was run to ascertain the correlation and its significance as shown in Table 3.

Table 3: Paired Samples Correlations

		N	Correlation	Sig.
Pair 1	SIWES & Project	361	.227	.000

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From Table 3, the $R_{SW\_scPR\_sc}$ Correlation and *p*-value were obtained as 0.23 and 0.000 respectively, suggesting that the correlation was significant at *P* = 0.05. We, therefore, reject the null hypothesis in section 3.3 and conclude that the correlation that exists between the IT courses is indeed not zero. The correlation matrix is further shown in Figure 2.

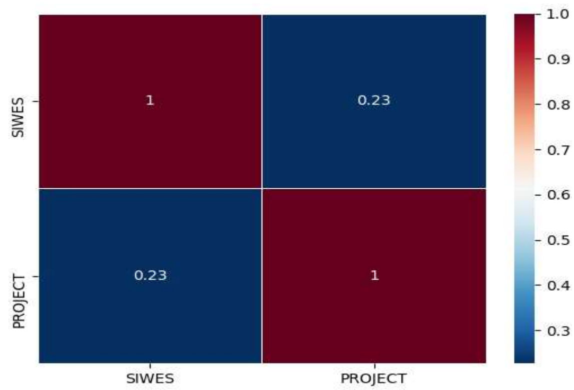

Fig. 2: Correlation Result Between SIWES, Project Scores

To fully understand the near zero (0) correlation between the SIWES and Project scores, the deviation trend between the two variables was computed. The deviation between the SIWES score and the Project score was also computed for each student. The negative and the positive deviations represent a decrease in score from SIWES to project and an increase from SIWES to project respectively. A positive deviation shows that the student has improved his SIWES score to reflect in his project score probably due to the training received. A negative deviation signifies a rather decrease in score from SIWES to project and probably means that the knowledge from SIWES was not applied by that student. Subsequently, the percentage decrease which shows the extent of negative deviation among the students was computed
The deviation was computed using equation 3 as follows:

$$PDT = \frac{\sum_{i=1}^{n} count_{of_{Increase}} - \sum_{i=1}^{n} count_{of_{decrease}}}{\sum_{i=1}^{n} count_{of_{increase}}} \times 100$$

$$PDT = \frac{179-1}{179} \times 100$$

PDT = -1.7% decrease in scores from SIWES to Project.

As a further test, a paired T-test was carried out on the data to find out if there exists any difference between the two IT courses as shown in Tables 4 and 5.

Table 4: Paired Samples Statistics

		Mean	N	Std. Deviation	Std.Error Mean
Pair 1	SIWES	64.0526	361	9.65401	.50811
	Project	64.8476	361	9.30362	.48966

Table 5: Paired Samples Test

	Paired Differences					
	Mean	Std. Deviation	Std. Error Mean	t	df	Sig. (2-tailed)
Siwes Project	0.79501	11.79016	0.62053	-1.281	360	0.201

Table 4 shows that across the IT scores, the mean of Project scores increased by 0.795. On the other hand, Table 5 shows that despite the average gain of 0.795% in scores from SIWES to Project IT courses, the significance value recorded as 0.201 is greater than 0.10 showing that the increase in mean was not significant. Based on this, the null hypothesis that there is indeed no significant difference between the two IT courses is rather accepted.

Finally, a performance comparison of the two IT courses was done. A look at the rate of performance was done using the grades of the students as a yardstick as shown in Figure 3.

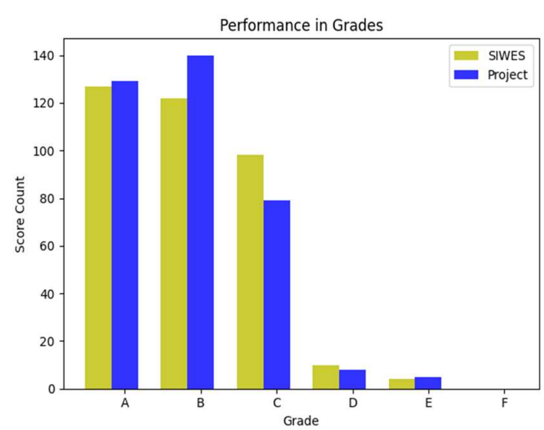

Fig. 3: Grade Performance Between The SIWES And Project Courses

Figure 3 shows that there were better grades like A's and B's in the project course than in the SIWES. However, in the lower grades like C's and D's, more students did better in SIWES than in Project.

Again, a look at the percentage of the students whose performance improved from SIWES to Project was done. Sadly, only 49.58% of the students showed some improvement from SIWES to Project. The majority rather did so well in their SIWES and failed to sustain the performance in the B.Sc Project. However, out of the 49.58% that showed an improvement, 70.11% of them are those that chose their B.Sc project topic in line with their experience in SIWES as reported in Table 6.

Table 6: Performance Analysis Percentage

Analysis summary	**Percentage**
Percentage of those whose performance Improved from SIWES to Project	49.58%
Percentage of those that picked their Project topic from their SIWES experience	70.11% (out of 49.58%)

The results of the KNN modelling are presented in Figures 4, 5 and Table 7, as shown. Firstly, the appropriate k = number of nearest neighbours to be considered. In other to do that, a plot of error against different values of *k* was done as shown in Figure 4.

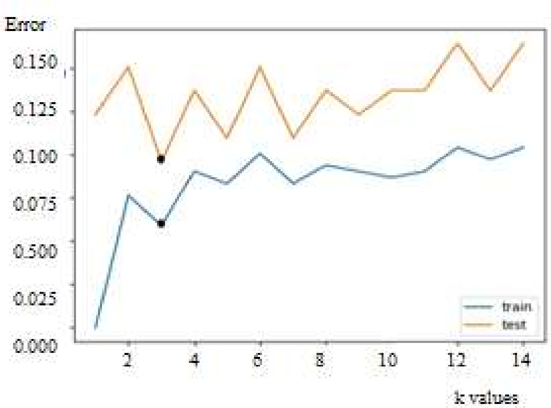

Fig. 4: Error Versus K Plot

From Figure 4, we observe that the test error begins to reduce from k = 2 to 3. At k = 3, it begins to rise again. On the other hand, the training error rises to k = 2 and begins to drop. However, it begins to rise again at the same k = 3. So our interest is to find a balance for k between the test and train data. This balance occurred at k = 3 and occurred again at k = 5. Hence k = 5 will certainly produce similar results. However, we choose k = 3 for the model.

To test the accuracy of the model, a confusion matrix was plotted for that purpose as shown in Figure 5.

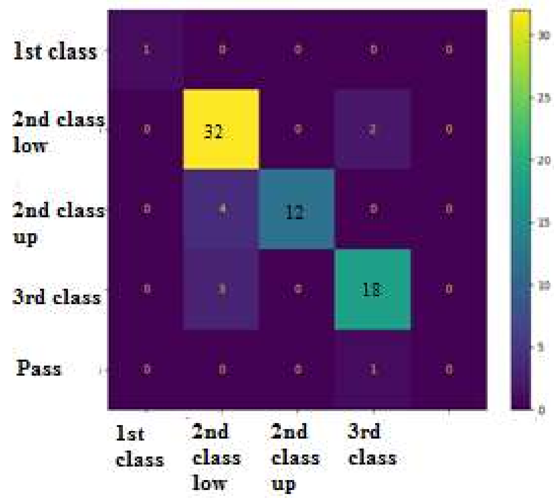

Fig. 5: Confusion Matrix Of The Model

The diagonal elements in the confusion matrix represent the total correct values predicted per class. It can be seen that 1 out of 1 student was predicted correctly for 1st class, 30 out of 34 for 2nd class–upper, 13 out of 16 for 2nd class-down, 20 out of 21 for 3rd class and 0 out of 1 was predicted for a pass.

Finally, a classification report for the model was also computed and presented in Table 7 as shown.

Table 7: Classification Report Of The Model

	Precision	**Recall**	**F1-score**	**support**
1st Class	1.00	1.00	1.00	1
2nd Class low	0.82	0.94	0.88	34
2nd Class Up	1.00	0.75	0.86	16
3rd Class	0.86	0.86	0.86	22
Pass	0.88	0.00	0.88	1
Accuracy			0.86	73
Macro avg	0.74	0.71	0.71	73
Weighted avg	0.86	0.86	0.86	73

Overall, the model recorded a prediction accuracy of 0.86 with k = 3. It predicted the 1st Class category with a precision of 1 while 2nd class upper and 2nd class down recorded a precision of 0.82 and 1 respectively based on the support values which were correctly predicted to be true. \The 3rd Class and Pass honours also followed the same analogy.

5. RESULTS AND INTERPRETATION

The correlation test between the IT courses gave a low relationship of 0.23. However, the relationship was indeed significant at $P = 0.05$. This signifies that there is indeed some relationship between the SIWES and Project. Hence, there is evidence that there is some level of cognitive knowledge transition between the IT courses. The result of a paired T-test which served as a confirmation shows that after engaging in SIWES which is the first IT course, the mean of Project (the second IT course) scores increased by 0.795. However, the little increase in mean was not significant to say with certainty that cognitive knowledge from SIWES is indeed a determining factor that influences the Project score. It rather reveals that most students do not transit the knowledge acquired in IT courses to improve on the subsequent ones. The performance analysis further supports this as only 49.58% of the students showed an improvement in the B.Sc Project performance score after their Industrial training programme. However, an interesting finding is that out of the 49.58% that recorded improvement, a whole lot of 70.11% of them are students that consequently picked a project topic that is related to what they learnt in their SIWES training. These students rather chose to apply what they learnt in the Industrial training in their Project thereby showing indeed that there is evidence that cognitive knowledge gained from an IT course could improve students' performance in another course. The findings are in line with [37] and [38] which emphasise the need for practical training as a means to prepare students to meet up with the dynamic and ever-growing demands of the labour market. The findings imply that considering the percentage of students that applied the cognitive knowledge gained from a previous IT course to a subsequent one and the success recorded, then one can comfortably say that the heavy government funds spent on Industrial Training schemes are justified. Hence the programme is still beneficial and ought to be sustained. In addition to all these, the KNN model gave an accuracy of 86% in predicting the class of honours of students based on the scores obtained in the IT courses.

5.0 Implications of the findings

The implications of the findings on students, lecturers and the government were discussed in this section.

5.1 Implications for students

Findings show that only a hand full of students take advantage of the skills they acquired during their industrial training to apply it in their degree projects. The few that apply the cognitive knowledge are however rewarded with wonderful and credible results. The degree project has a higher course unit of 6 and should be a strategic course for students who want to make a better class of honours. Unfortunately, most students usually do not make use of this advantage of picking a topic related to their industrial training, rather they end up picking new project topics which may not have any relationship with the cognitive knowledge already acquired from IT. In some cases, the students may not even be familiar with these new projects and they end up with poor grades for such a heavy unit course. Besides that, students who can further their knowledge from their industrial training to their degree project are opportune to be more equipped for the labour market due to their enhanced practical knowledge. The essence of practical training according to [37], is to prepare students to meet up with the dynamic and ever-growing demands of the labour market. It has also been discovered that a practical approach to teaching produces better results for the students [38].

5.2 Implications for lecturers

It is no doubt that the industrial training scheme is not properly monitored by the host academic departments. Often there is usually a disparity between the degree score of a student and the true performance. In such situations, high scores may be awarded to students who do not merit it while others are victimized due to irregularities associated with assessing the students. The authors in [39] believe that irregularities can distort the mechanism for assessment and may give a false outcome of a student's performance. Hence, given that the findings show that the degree core of students could be predicted from their SIWES score and course from other courses, this will assist in curtailing deviations arising from irregular assessments by the lecturers.

5.3 Implications for government

Considering the low correlation (0.23) between the SIWES and degree project scores, it shows that the heavy funds spent on the scheme are not fully justified. The government on its own should come up with educational policies that ensure that industrial training is fully put to use to improve the industrial value of the students. There is indeed not much connection between the scheme and the career value of the students. The scheme appears to be run disjoint from the hosting departments. Hence policies that improve the on-site assessment of these students by their lecturers should be welcomed. There should also be some academic certificate serving as proof of proficiency given to the students at the end of the training. Such certificates should be recognized an acceptable by industries. This will not only encourage the students and improve the value of the scheme but it will also sustain it.

6. FURTHER WORK

Although the results obtained in this work may have addressed the objectives and given credence to government heavy funding and continuity of the programme. It is however, heavily dependent on the data used for the analysis which may not have a holistic coverage. It is therefore recommended that a more detailed analysis could be carried out using a deep learning model on dataset from selected universities so as to compare with the findings of this work.

7. CONCLUSION

Previous work on this subject approached the problem from the point of predicting academic performance of students to improving the content delivery of IT programmes. However, in this work, the transitional effect of cognitive knowledge that Computer science students acquire through IT was measured based on the degree project and overall expertise. Hence, the findings of this work provides credence to sustain the funding and efforts on IT schemes as opposed to conjectures that the scheme has no effect on improving the labour quality of students.

The ability of Computer Science students to apply what they learnt in their IT programmes to their B.Sc Project was studied with a view of justifying the continuity of the programme in Nigerian Universities.. Findings reveal that the IT courses have something in common and that students who are keen to apply the cognitive knowledge acquired in their SIWES courses to their Project perform better than those who choose a different topic altogether. This finding therefore goes a long way to justify the funding of IT programmes and their continuity, especially for those in the field of Computer science

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