Empirical Study of Exporting a University Curriculum:

Is It Successful, Is It Profitable, and Is Student Learning Effective?

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ABSTRACT

Amidst unethical behavior scandals surrounding admissions and profit strategies of Western universities, stakeholders must wonder if exporting an American curriculum into developing nations will result in effective domestic student learning. The COVID-19 coronavirus pandemic interjected an additional unexpected constraint for higher education stakeholders, particularly for practitioners who were forced to move complex lab-based information system (IS) programming courses online for students in developing nations. The research question examined in this study was, would learning be effective in an American-African university partnership involving IS bachelor degree courses taught online to undergraduate African students during the pandemic? Hypotheses were developed from the peer-reviewed scholarly literature and tested using inferential statistics. Three pedagogy factors—design content, active engagement, and vocational motivation—along with demographic and experimental control factors were regressed on student learning using parametric statistical techniques.

KEYWORDS

Bachelor Students, Exportation, Foreign Teaching, Higher Education Policy, Pedagogy, Profit College, University Curriculum

INTRODUCTION

The authors conducted this study to address four research issues. First, the authors allege student learning may not be effective in information system (IS) bachelor degree courses because universities seeking to expand from western countries into developing nations may overlook student concerns in their quest for profits. The authors argue that student learning effectiveness, not profits, ought to be the central focus of stakeholders responsible for procuring cross-border online university products, particularly in vulnerable developing nations.

Second, the authors assert that student learning should be the main concern of a university (along with safety) even during a pandemic (i.e. the COVID-19 coronavirus), especially if the teaching platform shifts from a lab-based face-to-face context into a virtual online environment. Third, the authors assert higher education decision-makers, such as accreditation peer reviewers and students, must ask for proof of learning effectiveness when western profit-oriented universities with underlying

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market expansion strategies attempt to peddle their products into continental Africa's developing nations. Higher education professionals ought to sustain an ethical responsibility to at least ask if developing-nation student learning interests would be served by American profit-driven universities. Fourth, the authors found a gap in the literature, as there were minimal empirical studies measuring the learning effectiveness of cross-border university higher education partnerships, particularly with big American universities implementing IS degrees into African-based universities.

The above four controversial issues were explored in this empirical study where the authors examined student online learning effectiveness in an American-African university partnership involving IS bachelor degree courses taught online during the 2020 pandemic. Although the authors started this project with a research question predicated upon testing student learning effectiveness for information system (IS) degree courses in an American-African university partnership, the authors expanded this to address being forced to move the delivery of complex lab-based instruction online due to the pandemic. One challenge clearly highlighted in the literature was that teaching modern IS courses online is more difficult as compared to teaching the material in a classroom or lab (Strang & Vajjhala, 2017; Tsai, 2019). Thus, the authors were concerned if the IS bachelor degree courses were too difficult to teach effectively online, especially to developing-nation students. The authors' concern was that the challenge of teaching modern IS courses online was in addition to the difficulty of implementing an American-style IS curriculum into an African college.

The theoretical rationale underlying the authors' research was that the authors asserted cross-border higher education partnership models may face a challenge because of social culture, language, and learning style differences between the market leaders based in the UK, Australia, and the USA as contrasted with targeted developing-nation populations (Arnolda & Versluis, 2019; Strang, 2017; Ifeanyi et al., 2018; BC, 2020). In addition to the sociocultural differences between American versus African university populations, several recent studies have highlighted macro-economic restraints in some African countries including Boko Haram terrorism, government corruption, agriculture food insecurity, and other problems (Che et al., 2020; Chitiga, Kaniuka, & Ombonga, 2019; Ifeanyi, Irene, Justina, & Virginus, 2018; Kursh & Gold, 2016; Ortiz, Franco, Garau, & Herrero, 2017; Miliä, Vlajiä, Antoviä, Saviä, Stanojeviä, & Lazareviä, 2017; Strang & Vajjhala, 2017; Tsai, 2019; Ullah, Lajis, Jamjoom, Altalhi, Ghamdi, & Saleem, 2018; Yassine, Chenouni, Berrada, & Tahiri, 2017).

The research question examined in this study was: Is learning effective in an American-African university partnership involving IS bachelor degree courses taught online to undergraduate African students during the pandemic? The next section summarizes the relevant peer-reviewed scholarly literature to develop the hypotheses. Subsequent sections discuss the research design, methods, results, and implications.

LITERATURE REVIEW

Cross-Border University Partnership Strategies

There are many cross-border university partnership strategies, which are informed by marketing theories, for example starting with franchising, then importing, and finally direct investments. Higher education is unique as compared to physical or other products in that the institutional reputation as well as accreditation greatly impacts the product desirability. For this reason, multinational growth is most commonly used in cross-border higher education partnership strategies which require foreign direct investment to establish a university presence or a campus in a new country and if possible to use articulation agreements with credible partners to increase domestic enrolment. The strategy is implemented by foreign universities expanding into a country through a dual or joint degree articulation agreement, franchising with validation, building a branch campus, developing partnerships or collaborations, and or locally delivering online as well as blended programs (BC, 2020). A cross-border partnership can be applied by K12 schools as well as universities, colleges, and vocational institutions (BC, 2020).

Some developing countries collaborate with western-world nations for knowledge gain and credibility. Internationalization strategies in higher education have begun to fail due to rising global terrorism (Strang, 2019a), evolving political tensions (BC, 2020; Korstanje & Strang, 2018) and increasing restrictive government policies for travel visas (Korstanje et al., 2019).

Internationalization is a competing higher education strategy as compared to cross-border partnership. Internationalization strategies are commonly used by western-world nations such as UK, USA and Australia to attract foreign students to reputable universities who offer accredited degrees through various modalities which require some physical presence on campus (BC, 2020). The difference between internationalization and a cross-border partnership strategy is the latter is deployed by the domestic university, often in a developing country.

A third higher education growth strategy is global online, usually offered from a western-world country through the Internet to the world (including distance education variations), which does not require physical attendance (BC, 2020). Global online higher education strategies do not require consumer travel or international student visas but some online universities suffer from low credibility (Strang, 2019b), high-performing students often prefer at least some direct interaction learning styles with qualified professors (Strang, 2017; Strang, 2016) and unfavorable currency exchange rates or trade restrictions have negatively impacted tuition transactions (BC, 2020).

Due to these potential international student learning style differences, the authors hypothesized there may be difficulties teaching IS courses in American-African cross-border strategies due to the student origin or domestic campus location. The authors asserted that adopting a well-designed American-style IS curriculum at an African university would result in effective learning. The problem was the authors did not have a universal benchmark of learning effectiveness because local definitions could be much different than what stakeholders in other countries feel would be accurate. For this reason, the authors argued a valid learning effectiveness benchmark for an African university would be statistically equivalent grades between the African country college and its American partner campus. The authors felt this would show that learning would be effective, despite many potential contextual differences between the campuses. The authors felt if they could establish that student learning was equally as effective in an African university as compared to the American partner, then the authors would have a scientific basis for examining other cross-border partnership causal factors of interest.

Therefore, the authors created a set of control hypotheses designed to allow us to confirm that the dependent variable of student learning in the African population sample was more or less similar to the American population which the IS curriculum was adopted from. The authors considered these to be statistical control hypotheses at the course level. The first hypothesis was:

H1: African university student learning effectiveness would be no different compared to the American university partner.

Two additional hypotheses were developed for demographics control because the authors wanted to be able to prove there were no unusual critical differences between the two populations, namely age and gender since these were commonly measured attributes in social science studies. Therefore, the authors developed these two hypotheses:

H2a: mean African student age would be no different from the American population;
H2b: African student gender proportion would be similar to the American population.

Design Content, Topic, and Assessment Relevancy

Miliä and Vlajiä (2017) used an experiment to measure the ability of undergraduate science students located in Serbia to identify errors in software programs. This was a novel study with an applied focus. Their program was focused on programming process improvement, particularly object-oriented programming (OOP), using ISO/IEC 9126 software quality standards, and the lean software ideology. They argued quality is needed in computer science courses because students need to learn that software correctness is not the only outcome because quality means the end product must conform to software-quality standard metrics driven by practice and regulations.

In other words, the OOP is a tool but the more important goal is to develop a functional high-quality product that conforms to quality standards and end-user requirements. They conducted an experiment using 30 undergraduate students to measure how many software quality design metrics students could identify. Their study and design were not rigorous. They did not use statistical controls, the dependent variables were subjective and their sample size was small. Notwithstanding these limitations, the authors observed the course content factors were influential namely the topics, organization, sequence, learning objectives, structure, career link, relevant assessments, and ratio content as compared to testing.

Liu (2018) also published a study describing how blockchain was being taught to introductory computer science and business technology students. He described how he utilized a small Java application called ChainTutor to teach basic blockchain concepts in introductory technology courses. A justification for the authors' reviewing his paper was that he revealed how blockchain was becoming a focus in non-computer science fields such as banking, finance, health care, and general business. He advocated a visual approach for teaching this technical subject because the java application is a text-based command line environment although users can experiment with key blockchain concepts through a graphical user interface. He pointed out that students can generate keys, hashes, transactions, blocks, and wallets – which are fundamental aspects of blockchain. The authors thought it was relevant to cite how very technical subjects such as blockchain are being taught with visual models in addition to text-based programming languages. The authors' justification for this is that not all subjects have an OOP the authors need a fallback methodology for teaching certain topics in the computer science curriculum, at least until a new OOP is developed. The best practices from their study include course content factors such as relevant topics, sequence, learning objectives, structure, employee link, and relevant assessments or tests.

Goldstein (2019) published a single case describing how he designed a computer science course when not using an OOP. This was a qualitative case study with an effective outcome as the implied dependent variable but it had very limited generalization since it lacked any hypotheses or evidence. However, it caught the authors' interest for two reasons. First, he use a non OOP approach a text-based, namely the Raspberry Pi Linux text-based command line interpreter and Nano as the text editor, for all programming assignments. Although this was antithetical to the authors' study purpose, the authors felt it was the authors' duty to report all relevant approaches. The authors concur from their experience that the Raspberry product was useful for teaching and it may be used in other operating systems beyond Linux. He reported the students edited their programs using the Nano text editor, they submitted their programming assignments using SFTP, they configured and managed their Raspberry Pis, including installing and configuring the Apache web server, from the command line (Goldstein, 2019). From the authors' experience, the authors admit that was quite an accomplishment for bachelor computer science students. His best practices focused on course content factors to structure or organize the topics, make learning objectives effective, base content workplace contexts, and use relevant assessments to match learning goals.

Dekihara and Ochi (2019) used a mixed methods case study consisting of specialized pedagogy and the survey method, to explore the satisfaction of bachelor of science students in a non-engineering course in the Netherlands. Their paper outlined useful definitions of modern computer science curriculum topics including artificial intelligence, the internet of things, and robotics. The most relevant point they made was to use open-source software namely Ardublock and NNC/NNL as an OOP tool. The authors reported that using these two OOP tools was perceived as better by students based on a satisfaction survey. The findings were qualitative and limited in generalization due to their case study design. Nonetheless, their study was a good model for illustrating course design factors such as relevant industry-sequenced topics, matched academic-industry learning objectives, use of economical open source materials like the NNC/NNL, along with assessments matching the learning goals.

Darmoroz (2017) published a case study of curriculum design used for teaching mandatory machine language programming to a bachelor of science as well as a master of computational linguistics students at a German university. The course was positioned to service the field of computational linguistics professionals, referring to voice analysis research in the cognitive sciences. His study initially sounded interesting but there were no useful quantitative findings nor any insight into how to teach machine language programming. Their paper did promote good course design practices including appeasing industry requirements as learning objectives, sequencing topics organized in a relevant structure, and providing links to resource tools such as linguistics analysis software.

Tsai (2019) performed a quasi-experiment to determine if using a visual programming language (VPL) improved bachelor of science student learning as compared to the traditional lecture-based pedagogy with a text-based compiler. His sample size was 180 university students taking a programming course in Taiwan. His unit of analysis focused on student efficacy in programming and their understanding of basic programming concepts. Both groups studied basic programming concepts such as sequence, condition, and loops. The treatment group used the VPL while the control group used the command-level program. He used *a priori* instruments called the Test of Basic Programming Concept and a self-efficacy questionnaire to collect the data. He found the VPL improved student understanding of basic programming concepts in the experimental group and the effect was especially large in students with moderate and low self-efficacy (Tsai, 2019). The authors found his study relevant because it was an experiment with a large sample size and he used a modern OOP called AppInventor2 as the VPL. The authors felt his study demonstrated the need for good course design and modern content because he included many resources linked to the objectives and he leveraged AppInventer2 and other visual software tools.

Calvo and Cabanes (2018) published a four-year mixed-method case study of computer science bachelor students during their third year in Spain to report observations of using a project-based learning pedagogy for teaching mandatory IS courses from 2012-2016. The degree program was oriented to industrial electronics and engineering automation. Students worked individually and at times in team projects, in a format that the teachers felt reflected the workplace to develop skills needed by employers. For example, they required students to develop an embedded controller for a robot. Students built the robot using the Lego Mindstorms hardware kit using the OOP which according to Calvo and Cabanes (2018) is similar to the C++ programming language. Although promising, the study was limited because there were no clear statistical controls, the treatment pedagogy was not articulated, and the outcomes were subjective. In fact, according to Calvo and Cabanes (2018), their dependent variables consisted of two outcomes: Qualification marks and student satisfaction. The most relevant aspect of their study was how employers had influenced course design, to the extent that students worked on projects typical of engineering firms developing manufacturing control robots and systems. Additionally, they applied a largely unknown OOP called NXC but this was also a limitation because it is not generally used outside of the academic environment. Their paper emphasized the need for a modern course design and content referencing NXC OOP and learning objectives correlated with employment skills and performance needs.

Weiss (2017) published a brief action research case study where he explained how he applied OOP tools to teach a programming language to chemist students in a USA-based university. He used Python as the OOP language, Jupyter notebooks to share lectures, homework assignments, and project requirements. They downloaded a number of free common Python scientific libraries to process, analyze, and visualize data provided by Weiss (2017). The authors thought the most interesting aspect of his study was he used completely free open software and his students had no prior programming experience yet he claimed learning was effective. He discussed how the course introduced students to basic programming and applied skills for solving a variety of chemical industry problems. The authors also concur it was a good method to provide a large dataset, which the instructor knew well, so students could use it as the basis for them to use for learning the OOP. Therefore, the authors categorized this study as an example for good course design and relevant industry-related content, by focusing on applied chemical industry skills and setting goals relevant to assessments.

The Kursh and Gold (2016) paper was relevant to mention only because they emphasized using visual approaches to teach a blockchain programming overview in bachelor and master of business technology degrees. Their wholly theoretical paper made several salient points including that business students are interested in OOP just as computer science stakeholders are, but for different reasons. According to them, business students are interested in marketing opportunities balanced with the risk of security breaches, whereas computer science students are focused on providing solutions for marketing opportunities and addressing or preventing security breaches. The authors felt their paper was relevant to show there are stakeholders beyond computer science students when you are examining OOP. The authors classified their paper as having an inherent course design and relevant subject matter focus, due to the blockchain and cyber security content, and the link to satisficing industry stakeholders with the learning objectives.

Therefore, the authors created this hypothesis of composite factors to encompass the above:

H3: Design content factors in cross-border partnership IS courses will promote student learning.

Engagement and Active Learning

Moskal and Wass (2019) conducted an action research study to evaluate how effective interpersonal process recall (IPR) was to encourage students to think more about their software development processes. Their aim was to encourage undergraduate computer science students to reflectively think more about their software development processes, and what worked and what did not. They argued most programming courses focus on coding as a skill, mastering programming language syntax, but important tasks like planning, code design, code commenting, and error debugging was not taught enough. They argued planning and other processes cited above involved tacit thinking which was not emphasized enough in OOP. Therefore, they applied IPR to encourage students to think more about their software development processes. They argued IPR was optimal because it was developmental rather than evaluative, and it relied on a trained facilitator to guide the reflection in a structured way. They observed five undergraduate programming students, capturing their screens when they were working on programming assignments, and then presented the screen captures to students asking them to reflect on the experience. They found IPR was useful for revealing incongruences between the value students placed on certain development processes and what they actually do in practice (Moskal & Wass, 2019). The authors posit this is merely a manifestation of the planned versus actual behavior in that what people do is often different as compared to what they say they will do. The authors also feel the screen-capturing process may violate the ethical protocols of many IRBs and it is an intensive process, as can be seen by their small sample size of 5. Nevertheless, the authors concur with the general proposition that there is a plan versus do gap that needs to be reconciled in student learning. The authors also felt this study was novel to report because rather than study the OOP outcome they focused on the constructive feedback loop of active learning, mentoring, facilitating, mastery tutorials, incremental assignments for learning, and other tacit aspects of student engagement.

Rao and Dave (2019) conducted an action research study illustrating how they used a hands-on laboratory to teach block and encryption concepts to a bachelor of computer science and engineering students. They explained that computer science and engineering fields were undergoing rapid change due to advances such as the internet of things, cloud computing, and blockchain electronic transaction technologies. As they noted, this new demand has created a gap between traditional course material taught to students in B.S./M.S. programs at universities and the cutting edge of technology demanded by the financial and banking industries. They posited that a hands-on laboratory-based approach would be more effective in teaching the complicated blockchain programming topics because the instructor could guide and motivate them, while allowing them to experience a simulated physical but safe cyber security environment in the lab. They used Raspberry Pi, a small and inexpensive platform that allows students to build interesting internet-of-things (IoT) applications including blockchain end-to-end processing, acquiring images, creating immutable records using a cryptographic hash function, and transmitting and storing data on the cloud. They provided the preferred sequencing of mandatory material and software modules, but they allowed students to proceed at their own pace in between the lectures and labs. Their key finding was that students preferred instructor-guided hands-on laboratory exercises over theoretical lectures because, according to the authors, students were able to grasp concepts better when there was a short theoretical explanation followed immediately by related hands-on laboratory exercises (Rao & Dave, 2019). Although it was a qualitative study with no empirical evidence, they discussed active learning and student engagement delivery approaches including instructor-guided lab exercises interspersed with lectures, tutorials, and assignments, along with using technology such as Raspberry and IoT resources. Their study also emphasized the importance of including contemporary content such as blockchain.

Alkaria and Alhassan (2017) used an experiment to examine the effect of in-service training of computer science teachers in a graduate course by applying the Scratch OOP language in a learning management system platform (N=40). Pedagogically, they focused on teaching OOP skills along with attitudes toward teaching programming to future students. Their sample consisted of 40 middle school computer science teachers. Half the participants were assigned to the control group and the remaining 20 teachers constituted the experimental treatment group. The treatment involved using the Scratch OOP in an online platform along with labs and positive attitude lectures emphasizing the importance of the end user at the center of the design, with the control group allowed to simply complete the assignments in using the OOP without the positive attitude lectures. The measure consisted of an achievement test in Scratch programming language along with a survey of cognitive attitudes towards OOP instruction. They ran the experiment for two semesters. They found there were statistically significant differences between the achievement test mean scores in favor of the experimental group. They found the experimental group also attained higher positive attitude scores toward teaching OOP (Alkaria & Alhassan, 2017). Their results were relevant to the authors' study because using attitude lectures and labs as pedagogy for teaching OOP at the graduate level. The authors feel their study demonstrated active learning and student engagement principles of positive cognitive development, and motivation, leveraging OOP technology like Scratch, using assignments to enforce participation, and providing conceptual support for application design prior to the lab exercises using Scratch.

Erol and Kurt (2017) used a two-factor experiment to examine the effect of OOP pedagogy on student motivation and achievement in an instructional technology course at a Turkish university. The participants were 52 pre-service teachers, in the sophomore level. They divided the participants randomly into two groups, test versus control. During the first seven weeks of the study, the students in both groups were taught programming logic and basic programming structures. The test group participants used using Scratch while the control group applied the traditional techniques of flowcharting and problem-solving activities. During the second seven weeks of the course, the exact same method was applied bot the text and control groups, which was to use the C# programming language. The authors developed and applied an achievement test and a motivation survey to collect the data. They found the programming achievement scores for both the test and control groups increased at the end of the course. However, they reported the achievement test score increase was significantly higher for the test group using Scratch initially (instead of flowcharting). Additionally, they found motivation scores increased in the test group but decreased in the control group (Erol & Kurt, 2017). The authors felt this was a clearly-articulated statistically controlled experiment that proved that an OOP increased performance and motivation. However, the sample groups were small (N1=26, N2=26) which limits statistical inference and the effect sizes were small. The authors affirm the study sounded very useful to scholars yet it would need to be replicated. The authors chose this study because it emphasized active learning and student engagement principles of motivation, leveraging

OOP technology, using assignments to enforce participation, and providing conceptual support for the logic and programming structures prior to the tutorial exercises using OOP or flowcharting.

Saltan (2017) published a mixed-method experiment to assess if an online visual pedagogy was more effective to help students learn in a bachelor of science programming course, as compared to the traditional lecture-based approach with compiler languages. His unit of analysis was focused on the effectiveness of the online algorithm visualization (OAV) pedagogy, which uses an OOP in a real-time interpretative environment. He collected quantitative and qualitative data to examine performance along with perceptions, in a sequential mixed method design. The participants consisted of 40 IS students who were taking an introductory to programming bachelor of computer science course for the first time. Half of the students were randomly assigned to the treatment. During the first 4 weeks, the treatment group used OAV while in parallel the control group was taught the semantics of programming and algorithm through traditional lecture approaches. An achievement test consisting of six questions was used to measure IS students' performance in computer programming at the end of the course. The quantitative data were then analyzed using t-tests and ANOVA statistical techniques. They found the performance was significantly higher for the treatment group using OAV with the experimental group mean = 51.85 (SD = 20.34) and the control group mean = 38.75 (SD = 12.86). Next, in the qualitative phase, they administered an open-ended survey and semi-structured interviews to collect insights from the students about their learning. He performed a content analysis on the student comments, whereby five themes emerged: Students highlighted that OAV contributed to their algorithmic thinking (28%), progressive thinking abilities (7%), and OAV allowed for explorative learning (7%). He claimed students perceived OAV as an engaging instructional tool for learning computer programming (Saltan, 2017). While the quantitative evidence was clear in favor of OAV, the effect sizes were missing and the authors felt the qualitative results were weak as well as ambiguously described. The Saltan (Saltan, 2017) study modeled active learning and student engagement concepts such as visual learning style accommodation, critical thinking, algorithmic generalization, and exploration with achievement tests using OAV.

Friebroon-Yesharim and Ben-Ari (2018) published an action research case study of applying innovative pedagogy using robots to help teach computer science students. This was a well-articulated study, with an interesting agenda to assess learning on a six-scale learning typology by collecting data through four surveys at different points of time in the course. Their unit of analysis was to evaluate the Jourdain learning effect and the value of constructs (outlines) versus plans (designs). The participants consisted of 118 second-grade students in a mandatory computer science course. They used an educational robot with the accompanying visual OOP software development environment. They reported students learned basic concepts but were unable to create and run their own programs, so the Jourdain effect was not demonstrated because the students understood concepts and constructs but could not construct their own programs from the basic constructs (Friebroon-Yesharim & Ben-Ari, 2018). The authors reviewed this grade school study even though it was outside the population scope of university students because it had a large sample size and it focused on active learning and student engagement principles with tutorials, periodic assignments to enforce participation, leveraging technology including OOP or robots, and conceptual support for practical exercises.

Ortiz and Franco (2017) reported an action learning case study where they focused on stimulating motivation to inspire better learning in computer science students. They taught the older style C programming language in a course by having students assemble and program a low-cost mobile robot. The students were motivated because they could define the robot's behavior which provided immediate action as compared to the latent response loop of a graded assignment. The study was organized in small groups, with students programming the robots in teams, which allowed for osmosis learning and sharing of individual strengths to improve group outcomes. Theoretically, they applied the attention, relevance, confidence, satisfaction (ARCS) pedagogy learning model to catch and hold students' attention throughout the course, increase students' confidence in the learning process, achieve a high student satisfaction level with their acquired skills, and demonstrate to students the practical usefulness of the knowledge they had learned (Ortiz et al., 2017). They claimed there was a significant improvement in students' academic performance and motivation, but the authors did not observe any statistical evidence of that in the paper. The authors felt this study was relevant to cite because the authors emphasized motivation to stimulate student engagement, by applying the ARCS learning pedagogy, and using active learning principles including robot-based technology tutorials, assignments to enforce leveraging of individual strengths within groups and team participation, along with leveraging technology including the low-cost robot.

Giacaman and De-Ruvo (2018) completed an action research study with the goal to use an OOP for improving computer science student learning outcomes. They pointed out that programming was difficult for students entering a computer science program, largely due to the myriad of concepts and ever-changing programming languages. One salient point they made was that laboratory sessions provide an excellent opportunity for students to independently practice but that alone did not help them in the programming process as much as expert scaffolding would (Giacaman & De Ruvo, 2018). The problem is they did not prove that assertion. They did report students were more engaged with active programming exercises and they developed an inductive approach to learning, by focusing on developing problem-solving skills. A valid argument they posited was that students needed guidance in programming strategy rather than the syntax and peculiarities of any particular programming language (Giacaman & De Ruvo, 2018). The authors felt the most interesting point of their study was the use of the active classroom programmer (ACP) OOP software tool that placed minimal pressure on faculty resources because it is designed to improve student active learning and engagement. As noted, they utilized lab sessions and tutorials, along with periodic independent assignments to enforce participation, along with leveraging the ACP technology.

Canedo and Santos (2018) performed a retrospective quantitative assessment of bachelor computer science and engineering students at a Brazilian university followed by a survey of student satisfaction. The unit of analysis was how an active learning pedagogy and other factors including absenteeism, and active engagement impacted dropout rates, self-reported satisfaction, and grade in an introduction to computer science course. Their design was a correlation but it was unclear how they formed the active engagement factor and their effect sizes were small not to mention the sample size was also not large enough to be generalizable. The authors felt this paper was relevant because the authors observed a positive association between active participation/learning, student engagement, grade, and student self-reported learning satisfaction.

Ullah and Lajis (2018) published a brief meta-analysis of OOP-related automatic feedback programs that may be used to offload the grading process from instructors. He substantiated the need for this literature analysis as being needed because computer programming is high in demand, there were high student failure rates due to a lack of adequate programming skills, and there is simply too much work for an instructor to give detailed line-level feedback for every program to every student. They reasoned that instructors can use these automatic feedback systems to allow them to concentrate more on the areas where students need development scaffolding, instead of spending that same effort towards grading. They explained there were three theoretical approaches: Dynamic, static, and hybrid – they recommended the dynamic be used since it is immediate but the tradeoff was it requires more technology resources and runs on specific client platforms. Their paper is considered their paper exemplary of content because of the theory focus, and the link of objectives with industry requirements for the dynamic, static, and hybrid modern programming states of execution. The authors could also classify this study as emphasizing active cognitive learning due to the feedback look being used for grading, but not necessarily engagement.

Yassine and Chenouni (2017) reported an action learning study where they taught the C programming language to a bachelor of science students in Morocco. They focused on showing how game theory could be used to motivate students as a pedagogical approach. Thus, the authors selected this paper because it advocated game theory for student engagement and active learning, yet an OOP was not used.

Iskrenovic-Momcilovic (2018) published a quasi-quantitative correlation method paper where he analyzed the relationship between motivation, emotion, and pre-knowledge of students on the choice of method, mediated by age, abilities, and learning style preferences of students. He argued computer science students find it difficult to learn a programming language because it requires a completely different way of thinking from grade school. He posited a best-fit selection model could be developed using the tests for checking the given factors to identify the best approach. Unfortunately, his study was not clearly articulated, it was not robust, the authors could not replicate it, and his findings were limited to his own course. The authors felt the benefit to highlight was he implied a learning style rationale for customizing education in computer science programs by allowing students to methodically self-select a path, perhaps with alternative text versus visual OOP. The authors feel scholarly effort ought to be devoted to studying his idea.

Based on these papers, The authors developed this hypothesis of composite factors:

H4: Engagement and active learning factors in cross-border partnership IS courses will promote student learning.

Vocational Motivation

Agirbas (2018) developed a graduate-level course in which metaphors were used in the teaching methodology, allowing students to create their own designs while learning the basic elements of an IS OOP language in a short period of time through deductive reasoning. In his pedagogy, he taught a visual OOP language to undergraduates but he asked students to use a metaphor based on the architectural industry to serve as a prototype design context for their OOP assignments. Agirbas (2018) asked his students to apply an end-user perspective to design their OOP application. The significance of his pedagogy is a prototype focus (although he did not state that), as compared to the traditional OOP teaching concentration on language syntax and complex computer science concepts such as recursion or inheritance. Agirbas (2018) claimed his pedagogy was successful as far as students experienced all OOP design stages using a simple prototype, and most importantly students were able to develop their ability for versatile thinking and the use of more than one disciplinary tool in IS. The authors concur with his pedagogy. The authors suggest a simple OOP application could be prototyped, with a basic menu and data entry screen, processing, and display output.

The study by Agirbas (2018) was relevant to the authors' objective because the authors assert the goal for an IS programming principles or design course at the graduate level ought to focus on stakeholder needs rather than OOP computer science fundamentals. For example, the authors argue it would be more important in an OOP graduate course to teach end-to-end from design through to user quality assurance rather than focus on syntax or inheritance concepts of specific languages. The authors feel it is appropriate to focus on OOP language specifics in a bachelor or certification course. However, the authors suggest based on the authors' own industry experience to avoid teaching OOP language specifics whenever possible in graduate-level courses since technology changes so rapidly and graduate students are likely in senior analytical, team leadership or other decision-making roles as part of vocational employment. Instead, the authors argue to use a prototyping methodology, to select a contemporary simple OOP interpreter which emphasizes the design-build-test ideology, rather than the code-compile-debug iteration. However, his study had a weak qualitative research design and there was an insufficient explanation of statistical procedures. It was unclear if his results were based on rigorous testing as compared to subjective opinion. The authors felt Agirbas's (2018) study contained best practices for instructional delivery and vocational professionalism since it emphasized respect for stakeholder needs, employment skill expectations link communication, enthusiastic teamwork, punctuality or project management, and quality standards such as certification.

Boudia and Bengueddach (2019) conducted a quantitative quasi-experiment of junior-level computer science bachelor students in the Middle East to assess the impact of collaborative learning on OOP course outcomes over two semesters (N=108). It was an inspiring study but the design of their experiment was unclear which limited credibility and generalization. They grouped students into predetermined groups based on an unstated initial test and some additional (unstated) factor. The students are supposed to share the same programming assignment by distributing roles according to a global pedagogical scenario for OOP problem-resolving activities, while the professor observed how they performed their roles. The strategy for the problem-solving activities was to encourage the students to express their problems with OOP and then search together as a team for solutions. It was unclear how long this experiment took place or what the descriptive demographic statistics of the sample were. They created a questionnaire and used it to capture student motivation and satisfaction levels. There was no explanation of how the dependent variable was calculated. Nevertheless, they claimed students found cooperative learning beneficial (Boudia et al., 2019). Their study was relevant to us because they stated their faculty used old traditional and classical pedagogical methods to teach IS. Their approaches emphasized instructional delivery and vocational professionalism through project work, team problem-solving activities, communications, knowledge sharing, professionalism, and collaborative group learning, as would be needed in most workplaces.

The paper by Brehm and Guenzel (2019) was unique because they used COZMO the robot to teach introductory programming using Scratch and Python to bachelor students across several diverse disciplines including project management, computer science, and engineering degree courses. The robot was used partly to motivate and involve students. Theoretically, their pedagogy included active and collaborative learning with haptic experience reflection. By haptic experience, they hypothesized students would learn more by seeing animated characters interact with them instead of viewing the typical computer output from a compiled program. Collaborative learning was conducted by having students work in groups of 3-5 people to solve small OOP incremental projects throughout the course. The assignments were incremental, with each new one building on the previous one. The teacher purposively left out some information, such as how to capture data entry, in order to force students to search for the missing OOP elements. Hints were provided to avoid the student groups becoming discouraged when they could not solve a problem. In this way, they claimed the teacher was acting as their coach but the students were self-directed in their OOP projects. Unfortunately, their experiment was unstructured, there were no controls, and the measures were not revealed although grade may have been used as the dependent variable. Nonetheless, Brehm and Guenzel (2019) claimed using the robot increased interest in OOP. They reported that the teachers noticed an improvement in students achieving the overall course objectives (Brehm et al., 2019). The study caught the authors' interest because the participants were bachelor level yet they seemed to function well in the self-directed OOP group projects. The authors categorized their paper as instructional delivery and vocational professionalism because they included project work, team problem-solving activities, knowledge sharing, project management, collaborative learning, and haptic activities.

Chang and Yang (2017) created an experiment to determine if there was a relationship between the pedagogy of teaching a visual programming language to learn data structures and motivation. It appeared their sample contained bachelor of science students. They hypothesized student motivation would be increased when a visual programming language is used because it increases learning fun as well as learning effectiveness. A benefit of their research design was they included a pretest class, then for the remaining two sessions they counterbalanced groups with different order of treatments, the visual programming language first then the traditional programming language, and vice-versa, in a repeated measures approach, then finally examining motivation after each session. They used a survey to have participants self-report their motivation. Change and Yang (Chang et al., 2017) found motivation had a stronger positive relationship with the visual programming treatment, but the traditional programming language had a higher relationship with motivation as compared to the pretest stage before any language was taught. Although they claimed the use of a visual programming language in a data structure course had a significant effect on improving learning motivation, statistically, their experiment could prove only a relationship, not a cause-effect. Nevertheless, the authors were interested in their study because it corroborated many others where student motivation was higher in computer science courses when the pedagogy addressed visual learning styles along with instructional vocational employment and professionalism requirements.

Shi and Cui (2018) published an experiment to study the impact of applying roles to improve bachelor of science student performance when learning the C programming language. The most interesting aspect of their study was the structure of observed learning outcomes (SOLO) taxonomy to organize their course and to categorize each of the tested aspects. They divided participants into treatment and control groups. The students from the control group learned programming in the traditional case-based teaching method while the students in the treatment group learned programming by applying the role-based approach. The role-based approach required each student to take on a specific task in the team, such as designer, coder, and so on. In this way, the individual strengths of each student were leveraged to overcome specific weaknesses and to improve the overall combined effort of the group. They leveraged the SOLO taxonomy to evaluate the student's final paper-pencil test. They graded the code reading and code writing test questions according to comprehension and construction based on the SOLO categories. They found there was a higher level of performance and cognitive ability in the treatment group. There were some significant positive correlations between final exam scores and the SOLO scores (Shi et al., 2018). This was an empirical study and it provided some evidence of learning effectiveness. The authors felt this was a good benchmark empirical study with strong evidence linked to a theoretical pedagogy framework. However, the authors argue it is a subjective process to grade a written student paper to evaluate their programming competence, and they did not publish inter-rater statistics or other effect sizes. Few of the other studies the authors reviewed were able to articulate a specific pedagogy or theory underlying their experiment. Their advice was clear to have an instructional delivery and professionalism focus on employment skill needs such as group collaboration, team role development, communications, project-based environment simulation, punctuality, quality assurance, and business case-based reasoning.

Chitiga and Kaniuka (2019) used the survey method to examine the relationship among 21 learning factors including time management, memorization study, and test-preparation habits. Their sample consisted of 86 first-semester African-American college freshmen in a bachelor of science program. They found students believed the sufficient time was being spent studying although many participants reported being unable to study for long periods, some had knowledge retention challenges, and those students with poor study habits generally were cognizant of their haphazard approaches. Not surprisingly, they found there was a strong relationship between having disorganized study behavior, cramming, and difficulty in knowledge retention (Chitiga et al., 2019). They recommended faculty spend more time helping students develop better study habits. One key limitation of their study was their questionnaire collected all data so the students self-reported their time management, note-taking, test preparation habits, and retention of knowledge. This means the data were subjective and all came from the same source at the same time – the participant. No actual objective outcome was cited such as a test score, time spent in a learning management system or grade. Another potential issue with their study was that only an unknown proportion of participants had poor study habits, so the authors do not know which factors could have been helpful to the more successful students. It could be stated that generally teachers already know some students in certain socio-economic or socio-cultural groups tend to have poor study habits so the scholarly focus is usually on how to improve that as the unit of analysis rather than reiterating what the authors already know. This study reminded us of the need for good instructional delivery and vocational professionalism, as they emphasized project management, organization, self-regulation, good study habit development, punctuality, quality standards for knowledge acquisition, and learning determination.

Based on the above studies, the authors developed this hypothesis of career-related factors:

H5: Vocational motivation factors in cross-border partnership IS courses will promote learning.

METHODS

The authors held a pragmatic ideology which according to Strang (2015) is a combination of the fact-driven post-positivist philosophy and the willingness of the researcher(s) to integrate or adjust statistical techniques to achieve goals while maintaining scientific rigor. An additional justification for the authors' ideology was this was an exploratory study given there was very little *a priori* literature about teaching IS using the new cross-border partnership strategy in Africa. Therefore, the authors took advantage of an opportunity to ethically collect data, so the authors' sample was small at 30-100 despite the authors' intention to use inferential statistical techniques. The authors' dependent variable was student learning, the grade reported by the student. The authors used the GPA from an American partner, converted to a 5 point scale, as the learning effectiveness benchmark. The authors developed numerous hypotheses based on the independent factors from the authors' literature review, and as discussed later, the authors categorized them into five categories.

The unit of analysis was the causal factor relationship of demographic and pedagogy factors on student learning in several IS programming language courses within the unique context of an accredited sub-Saharan university deploying a cross-border partnership strategy based on an American-style IS curriculum. The authors used the 95% level of confidence for all tests. The authors used descriptive statistics, reliability analysis, partial correlation, semi-partial correlation and stepwise linear multiple regression in SPSS to test the authors' hypotheses. The authors executed some of these statistical techniques multiple times after eliminating insignificant factors to create a parsimonious model.

Study Site and Sample Participants

The authors selected the case study site because it offered very unique higher education market characteristics and it was convenient since the authors had an opportunity to conduct this research with IRB ethical approval during the pandemic. This higher education market was of interest to us due to its significant economic footprint. The authors' reasoning was that if a western nation for-profit university were contemplating a market expansion, then this developing country could be prosperous for higher education products as compared to the Middle East, Asia, South America, or Europe, especially given the severe coronavirus impacts on India's, China's and Brazil's economies. Nigeria is Africa's largest economy with a GDP of over $410+ billion by 2019 and it is the most populous country in the continent with an estimated population of nearly 200 million people (Nigeria-NBS, 2019). Demographically, the country is young, with 62.5% of the population under the age of 24 and having a relatively high average annual population growth rate of 3.5% (Nigeria-NBS, 2019).

When Nigeria gained independence from the UK in 1960, the country had already established six research-focused universities yet as the demand for graduate degrees increased more universities emerged. UK and USA-based universities initiated cross-border partnership strategies with Nigerian institutions as a method to gain a larger market share and increase revenues – and vice-versa (Waddingham, 2018). Thus, there were clear benefits for an American university to expand into this country for IS degree market expansion and profit purposes. Actually, there were plausible benefits for the host African country too. The key benefits of a cross-border partnership for a host African university included: Access to advanced online course designs, modern syllabi, research resources, IS design content, IS programming languages, IS faculty mentoring, pass-through accreditation from USA or UK, and subsequent instant credibility with IS higher education consumers (Waddingham, 2018).

The African host population was the American University of Nigeria (AUN). AUN was founded in 2003 by Atiku Abubakar and the Adamawa Peace Council as a not-for-profit institution, Nigeria's former vice president, along with other local and international statesmen and academic leaders. Dr. Dawn Dekle succeeded Dr. Margee M. Ensign as president of AUN on July 1, 2017 (http://aun.edu.ng). The university is located in northeastern Nigeria in Yola, in the state capital of Adamawa. AUN is a residential campus situated on 2,400 hectares. AUB enrolls approximately 1,400 undergraduate students annually and they employ 87 faculty members. AUN is accredited as a member of the Association of American International Colleges and Universities and the Global Liberal Arts Alliance.

The university was originally named the ABTI of Nigeria but changed its name in 2005 as it deployed a cross-border partnership strategy through collaboration with American University based in Washington DC, USA (Ensign, 2012). Former president Ensign (2012) recounted that AUN became known as a bright spot on Google Maps due to their 24x7 power and internet service, to the extent that a Google team traveled to Yola to study this anomaly. She explained that AUN deployed the American-style teaching and curriculum model, they installed fiber optics providing high-speed internet access to campus stakeholders, and students used e-books almost exclusively.

Ensign (2012) complained that relatively few USA or UK-based universities were initiating cross-border partnership strategies with institutions in Africa ─ where the need was greatest. She explained the choice of an American style pedagogy and degree-course structure was because the university's founder and leadership team thought this was the best alternative in the world at the time (Ensign, 2012). Yola is known as a place of harmony, populated by half-Christian and half-Muslim residents living peacefully for generations, yet the entire country has been ravaged by climate change, plagued by food insecurity, and terrorized by Boko Haram (Che et al., 2020). One of the most unique attributes of AUN was that students are required to do community-based projects in parallel with their academic courses (Ensign, 2012). It took several years to fully implement the American-style curriculum which was complete by the time of the authors' study in 2020. The problem was no one could have predicted the coronavirus pandemic. Teaching IS online was a challenge so AUN stakeholders wanted to study student learning effectiveness.

The authors' study was situated within the School of Graduate Studies, and specifically, the School of Information Technology & Communications at AUN, which offers among other degrees, information systems (IS) master's degrees, PhD in IS, an MBA, and a PhD in business administration. The scope of the authors' study was the master of IS degree program which was focused on IS. The authors gained permission to survey students over three IS courses: Programming Principles, Program Development, and Software Design Architecture. The same student cohort progressed through these courses guided by the same professor in the same class and lab environment. A previously validated instrument was used to collect data from the students. The course opinion survey (COS) was developed by the American university, approved by the USA-based accreditation institution and adopted by AUN. After the end of the courses, the authors asked participants for responses to the COS independent factors using a 1-5 interval scale (where 5 was the highest) and the authors asked them to provide their grades as an indicator of learning effectiveness.

RESULTS

Most of the students in the authors' sample were domestic by nationality with less than 5% reporting international ties. The sample had more male students (62%) than female (38%) but this was comparable to the higher concentration of males in the IS programs in the authors' collaboration partner university. The higher concentration of males in the IS program was reflective of the national trend where there were more males in the computer science discipline. Most of the students were 18-20 years (i=19.03, *SD*=1.11).

Table 1 lists the descriptive statistics for research variables with a brief literature-driven definition, grouped by hypothesis and sorted by descending mean (*M*) with standard deviation (*SD*). The authors serialized all 18 variables using the convention of a mnemonics prefix signifying the *a priori* theoretical foundation plus a database-wide sequential number for traceability. For example, Tutor18 referred to using mentors or tutors and it was variable number 18. The authors also randomized the order to improve instrument reliability so the items are not necessarily serialized by factor.

The authors first verified overall learning effectiveness met the basic standard of the western partner. To accomplish this the authors tested Learning15 (*M*=4.596, *SD*=0.198) against the assurance

Table 1. Descriptive statistics grouped by hypotheses factor with brief descriptions, mean (1-5 scale), SD

Hypothesis	Variable	Brief survey item explanation	Mean	*SD*
H1: Benchmark	Learning15	Measure of learning effectiveness, sub-Saharan Africa site, dependent variable	4.5957	.19837
H2: Demographics	Age19, Gender20	Mean ages and proportion of gender for sub-Saharan Africa site, Male=62%, Female=38%	19.03	1.22
H3: Design-content (topic relevancy)	Organize01	Organized topics with relevant industry-like performance assessments	4.7239	.08390
	Syllabus02	Learning outcomes, objectives, sequence, assessment policy clear	4.6195	.14037
	Content03	Topics driven by IS industry, IS practices and literature	4.6144	.11094
	Assessment04	Assessments related to industry topics, material covered, practical format	4.6337	.24181
	Objective05	IS content modern with OOP, security, decision making theories/tools	4.7744	.10640
H4: Active-engagement (hands on activities, team projects)	Participate13	Active participation in class sessions, tutorials, exercises, team work	4.5975	.29359
	Assignment14	Student active participation in individual or group assignments, tests, meetings	4.6063	.28662
	Technology16	Leverage IS including OOP, devices, laptops, servers, software, hardware	4.8098	.19152
	Library17	Utilization of books, manuals, library computers [not retained in model]	4.1494	.32008
	Tutor18	Learning support including tutors, excellence centers, mentors [not retained]	4.0608	.58600
H5: Vocational-motivation (career links, workplace expectations)	Lecture06	Industry-relevant presentations, certification standards	4.7000	.06286
	Communicate07	Individual, team, stakeholder communication skill modeling	4.5698	.08660
	Stimulate08	Motivation, enthusiasm, stimulation, interest, enjoyment, satisfaction	4.5342	.18136
	Knowledgable09	Knowledge creation and sharing	4.7537	.08474
	Research10	References to industry practices, OOP materials, supplemental documents	4.7392	.08924
	Professional11	Professionalism, ethics, quality assurance, integrity, honesty	4.7800	.16487
	Attitude12	Positive attitude, workplace expectations, perspective taking	4.6227	.18296

of learning American partner benchmark of 4.5 (SD=0.6) using a two-sided one-sample t-test. The authors used the parametric technique rather than the distribution free Wilcoxon alternative since both data types were interval. The result was not significant, with a t-test coefficient of 0.9 (DF=83), p>.05 (two-sided). Thus the authors accepted hypothesis H1, African university student learning effectiveness would be no different compared to an American partner university. The authors determined the mean student age and gender proportions were statistically equivalent. Thus, the authors accepted the hypotheses that African university student mean age (H2a) and that gender proportion (H2b) were statistically similar to the American partner university population.

The COS was previously validated by the American university, using principle factor analysis. Therefore the authors wanted to verify the data fitted the *a priori* factor model loadings using a variation of confirmatory factor analysis. The authors also conducted reliability analysis on all cognitive type of data items to ensure the questions were valid and reliable measures of each factor group since the COS was given to a new population with a different culture. All reliabilities were acceptable. Specifically, the Cronbach alpha for the 'content design' factor (linked to hypothesis H3) was 0.759, it was composed of five items with a mean of 4.673, a significant $p<.001$, average interclass correlation of +0.759 (DF=83,332), and Hotelling's $T^2(4,80)=273.717$, $F=65.956$, $p<.001$. The Cronbach alpha for 'active engagement' (linked to H4), was 0.915 with three items (after dropping two), with a mean of 4.47, an average interclass correlation of +0.915 (DF=83,166), and Hotelling's $T^2(2,82)=89.404$, $F=44.164$, $p<.001$. The authors dropped Library17 and Tutor18 due to their low loading on the factor. The Cronbach alpha for 'vocational motivation' (linked to H5), was 0.659, and it was composed of seven items with a mean of 4.671, a significant $p<.001$, average interclass correlation of +0.659 (DF=83,498). It had a Hotelling's $T^2(6,78)=296.147$, $F=46.385$, $p<.001$.

The authors created three variables to represent the factors, and the authors populated them using the mean using the 16 of 18 retained items from the reliability analysis, which were summarized in table 1. Design-content represented course design, topic, and assessment relevancy, with a mean of 4.67 (SD=0.105). Active-engagement was intended to capture student engagement and active learning, which had a mean of 4.52 (SD=0.168). Vocational-motivation measured course vocational skill and workplace professionalism alignment, which produced a mean of 4.66 (SD=0.079). The authors applied linear regression and partial correlation to test the remaining hypotheses.

The regression was successful, resulting in a statistically significant model showing design-content, active-engagement and vocational-motivation predicted student learning. The model had a very high effect size of 87% indicating the amount of variance in learning explained by the three factors. The omnibus model fit estimates were: $r^2=0.870$ (adjusted $r^2=0.865$), $SE=0.0729$, $F(3,80)=178.15$, $p<.001$ (significant). The other important regression estimates are summarized in table 2.

The design-content factor had a beta coefficient of -1.038, with a $t=-5.63$, $p=.009$ (significant). The standardized beta coefficient was -0.551 and the largest in the model yet only slightly higher than active-engagement. The authors accepted the hypothesis (H5) that design, topic, and assessment relevancy of the course predicted student learning. The active-engagement factor had a beta coefficient of +0.560, a standardized beta of +0.473 (second largest in the model), $t=7.781$ and $p=.000$ (significant). The authors accepted the hypothesis (H4) that engagement and active learning in the course delivery predicted student learning.

The third factor vocational-motivation had a beta coefficient of +0.282, $t=1.286$, $p=.202$ (not significant). This factor had a smaller standardized beta of +0.112 and it was unfortunately not close to being significant. Therefore, the authors rejected the hypothesis (H3) that vocational skill and workplace professionalism in the course could predict student learning. The partial correlations and tolerances were low while the VIF was high for this factor, which indicated to us underlying problems in the authors' model fit, likely due to factor collinearity.

Given the strong performance of only the first two variables, the authors followed the advice of Strang (2015) to record the hypothesis results and then optimize the model using only significant predictors, so as to allow other scholars to extend this research. The authors applied stepwise linear regression, to check the incremental effect size, partial correlations, and variance inflation estimates of both significant factors, yet allow the third to be entered to validate model fit.

The stepwise regression results were very good, with the estimates listed in table 3. The model fit estimates for the first model with only design-content were: $r^2=0.726$ (adjusted $r^2=0.722$), $SE=0.105$, $F(1,82)=217.012$, $p<.001$ (significant). When the active-engagement was entered, the variance captured increased by 14.1%, with model fit estimates of $r^2=0.867$ (adjusted $r^2=0.864$),

Table 2. Regression coefficients and estimates of three-factor impact on student learning (N=84)

Factor	Beta	*SE*	Standard	*T*	*P*	Zero	Partial	Semi	Tolerance	*VIF*
(Constant)	5.602	2.077		2.697	.009					
Design-content	-1.038	.184	-.551	-5.630	.000	-.852	-.533	-.227	.170	5.881
Active-engagement	.560	.072	.473	7.781	.000	.719	.656	.314	.440	2.275
Vocational-motivation	.282	.219	.112	1.286	.202	.535	.142	.052	.213	4.691

SE=0.0732, *F*(2,81)= 264.267, *p*<.001 (significant). The key stepwise regression estimates for the best model are summarized in table 3. Design-content increased the beta coefficient to -1.248, the standardized beta rose to -0.66s2, with *t*=-14.603, *p*=.000 (significant). Active-engagement slightly decreased the beta coefficient to +0.498, the standardized beta was down to +0.421, with *t*=9.282 and *p*=.000 (significant). The partial correlations and tolerances were higher in this model and the variance inflation factor (*VIF*) estimates were all low – these were desirable findings indicating the estimates in table 3 represented a better model.

Table 3. Stepwise regression coefficients estimates, two-factor impact on student learning (N=84)

Factor	Beta	*SE*	Standard	*T*	*P*	Zero	Partial	Semi	Tolerance	*VIF*
(Constant)	8.176	.553		14.789	.000					.553
Design-content	-1.248	.085	-.662	-14.603	.000	-.852	-.851	-.591	.797	.085
Active-engagement	.498	.054	.421	9.282	.000	.719	.718	.376	.797	.054

DISCUSSION AND CONCLUSION

The authors achieved the authors' goal to show that student learning was equally effective for IS graduate courses at an African university implementing a cross-border partnership with an American university. A parametric two-sided one-sample t-test determined that African student learning was similar to the American partner university population (N=84). The authors' preliminary three-factor solution captured 87% of the variance in student learning, but one factor was not significant. The authors' optimized causal model based on stepwise linear regression was significant with an 87% effect size.

The authors found student demographics such as age or gender did not impact student learning in this cross-border American-African university partnership context. The authors tested age and gender to remain comparable with the descriptive statistics reported by Waddingham (2018). To that end, the authors' results that age and gender did not make any difference for student learning in IS course were in agreement with the market segment expectations since the authors' students were relatively young with little variation. The mean student age was 19.03 (*SD*=1.22). The gender proportion was 68% males and 32% females in the authors' sample. The authors' results for age insignificance somewhat contrasted with Iskrenovic-Momcilovic (2018) because he found age was a mediator of motivation, not learning, in his a quasi-experiment. The authors posit his sample may have included older students because the population was not a developing nation. Additionally, his dependent variable was motivation not learning. None of the other researchers in the authors' literature review reported any significant effect of gender or age on student learning so the authors assert the authors' findings of no gender effect and no age impact were in line with comparable IS degree studies.

Unfortunately, the authors had to reject the hypothesis that vocational motivation in IS courses predicted student learning. The authors' finding related to vocational motivation not being related to student learning sharply contrasted with the studies the authors reviewed. In particular, the findings were opposite to Boudia and Bengueddach (2019). Their study was one of the few statistically robust designs reviewed for this factor and their sample context was similar to ours. They conducted a quantitative quasi-experiment of junior level computer science students and found vocational motivation factors improved student motivation and performance.

The authors believe the low impact of vocational motivation factors on student learning in the IS course could be due to lack of student workplace experience, their immaturity, and socio-cultural differences between emerging information science graduates in the sample as compared to the embedded course pedagogy of the western partner. For example, although the student ratings were high for most items in the vocational professional factor (see table 1), with means ranging from a low of M= 4.5 (SD=0.18) for Stimulate08 (e.g., motivation, enthusiasm) to the highest of M=4.8 (rounded, SD=0.16) for Professional11 (e.g., ethics, quality assurance, integrity). Statistically, the authors argue these were high student perceptions but on an individual level they did not correlate directly with learning. The authors believe this high student perception of professionalism, ethics, honesty, stimulation could be due to the well-known corruption problems in Africa (Che et al., 2020) where students may appreciate the different professionalism philosophies and practices of USA and UK educated faculty in the IS program. The authors wanted to explain the authors' comments, being that many domestic professors obtained degrees from outside Africa, and in the current study the authors were research-participants with education from USA. Although the authors' IS career-driven design content the authors may have been viewed positively by African students, with regards to vocational motivation, the problem was it did not statistically impact the authors' student learning.

The authors looked further into the issue of vocational motivation not predicting student learning. The authors observed Communicate07 (e.g., stakeholder communication skills) had a relatively low mean of 4.57 (SD= 0.09) as did Attitude12 (e.g., workplace expectations) M=4.6 (SD=0.18). Relatively lower in this situation is relative to the higher factor item means of 4.7 for Lecture06 (Industry-relevant presentations), Knowledgable09 (e.g., sharing) of 4.7, Research10 (e.g., industry practices, OOP materials) at 4.7, and as cited earlier Professional11 at 4.8 (rounded). So, in summary, the student perceptions were relatively lower for stimulating motivation, stakeholder communications, and workplace attitude expectations. The authors think these lower perceptions were due to the lack of experience with workplace best practices as built into the IS course by the USA-based university, and therefore simply a socio-cultural difference. This was an early life-cycle cross-border partnership program so the authors conclude some best practices adopted from the host college will take longer to appreciate. Sometimes faculty will accept best practices to remain accredited even though they may feel slightly at odds with the domestic business style. The authors do not infer the USA-based best practices are poor, just that it will take a longer time in the life cycle to fully accept, at least from the student perspective. At the other end of the pedagogical continuum the authors observed student perceptions were relatively higher for some vocational motivation ratings, namely professionalism-ethics, knowledge sharing, and industry research practices (from table 1). These higher-rated items may tap into a growing African student awareness of the need to overcome corruption, and to share knowledge as well as research at the national level. The authors believe the internet and social media have educated African students about national issues and they see an IS degree as a means to a better end, therefore, they feel positive about those aspects in the course pedagogy. The authors think the students appreciate having well-educated faculty with high professionalism, a knowledge-sharing ideology, and well-stocked with relevant IS research to give away. Overall, the unbalanced lower ratings of some industry expectations with the higher perceptions of national career improvement game-changers, cannot be used statistically to predict student learning, at least in the authors' linear model. Perhaps if the authors ignored one of the other inter-item components (industry expectations versus national improvement dreams), the authors could develop a significant model. However, that does not meet the authors' scholarly goal. The authors could maybe divide the vocational motivation factor into two variables, perhaps in a future study. The authors highly recommend that and will look into it.

On a positive note, the authors found the two other factors could predict student learning in IS graduate courses at the accredited African university following a cross-border partnership strategy with the American partner. The final two-factor model developed using stepwise linear regression was statistically significant with a very large 87% effect size to account for student learning. The authors found IS course design content could significantly predict student learning, but students who liked the design did not do as well as those who ignored it. The authors also found pedagogy focused on active engagement during the online IS course could significantly predict student learning.

The authors argue the authors' findings that active engagement improved student learning make theoretical sense according to good pedagogy practices. The active engagement factor captured participation captured activities such as instructor tutorials, teamwork that was graded as a group, mandatory active participation, and teaching with IS tools like visual OOP software. The three items comprising active engagement from table 1 show high means, namely: Participate13 (e.g., active participation) M=4.6 (rounded, SD=0.29), Assignment14 (e.g., group assignments), M=4.6 (rounded, SD=029), and Technology16 (e.g., leverage IS/OOP), M=4.8 (rounded, SD=0.19). In fact, Technology16 had the highest mean of all variables, which the authors argue shows high student satisfaction with the OOP approach for teaching and this could have escalated the positive influence on most other items in this factor group.

The authors' findings for active engagement being able to predict student learning corroborated most of the literature that the authors reviewed for this factor. In particular, the findings for student active engagement supported the results of comparable statistically-rigorous studies. For example, Alkaria and Alhassan (2017) found active student engagement pedagogy had a significant impact on learning in an experiment using computer science teachers in a graduate IS course. Erol and Kurt (2017) also found student active engagement factors improved student achievement and motivation in an experiment of 52 pre-service IS teachers. Furthermore, Saltan (2017) found active learning principles including an online active visualization tool positively impacted student learning in an IS course, although the authors felt his quasi-experiment was not as robust in design as the above two.

Delving further into the results, there was one unusual finding which theoretically contrasted with the *a priori* literature and with the authors' philosophical assertions. The problem the authors found was IS course design content varied negatively with student learning. Design-content was the strongest predictor in the authors' two-factor model, with a negative standardized beta coefficient of design-content -0.662 (see table 3). This finding can be interpreted as higher satisfaction or agreement with the course design resulted in lower student learning, and vice-versa.

To explore this unexpected finding of course design varying negatively with student learning, the authors first examined the factor items from table 1. The authors observed the ratings were relatively high in comparison to the other two factors, with the highest being Organize01 (relevant industry topics), M=4.7 (SD=0.08) and the lowest was Syllabus02 (learning objectives/sequence), M=4.6 (SD=0.1). There were no significantly different item ratings within the factor, and again in a relative sense, these were high scores on a 5 point scale. The problem from a statistical basis was that individually the student course design ratings did not correlate directly with student learning. This was different from the earlier problem with vocational motivation, wherein students were polarized to some extent on the industry expectations/communications (being lower) versus national career aspirations including professionalism (being higher). There did not seem to be a polarization of student perceptions within the design factor, and statistically the authors argue this was proven by the significant regression estimates (see table 3).

Furthermore, the authors believe a portion of students thought the course design was comprehensive and they paid a lot of attention to it, perhaps more attention than the faculty. In contrast, the authors think other students, perhaps those with higher programming competence, but they ignored most of the course design components (except the grading aspect) and instead those students concentrated on the active learning activities to write programs. This is the key to explain the problem, being that the authors feel students who concentrated more on the activities and less on syllabus requirements, actually learned more through programming, and vice-versa, those students preoccupied with understanding the policies, industry topics, and learning objectives, did not put so much effort into programming. Another explanation, in addition to the above, is the authors feel the faculty used the western partner syllabus an inherited the course design, but they may not have cognitively adopted everything to the degree that they implemented necessary syllabus requirements (e.g., graded items) but chose to apply their expertise to mentor and teach students the art of OOP. Faculty and students may have experienced the cognitive load factor of a verbose western country-based syllabus and chose to focus more mental energy on programming and interaction activities. The authors believe other scholars could examine this phenomenon by capturing how much time students spend on following the course design components as compared to participating in active learning activities.

Finally, the authors looked into why two IS course items were unreliable in the active learning factor. Library17 (library books/manuals) had a mean of 4.1 (*SD*=0.3), which was the second lowest rating in the data (see table 1). The authors observed many students used their smartphones to hold PDF copies of OOP manuals and students would often search the internet for solutions to syntax problems or for data structure subroutine best practices. This could explain the lower ratings for using the university-provided resources like OOP manuals from the library. The authors think a few students used the library materials, but given the authors' small sample size, this would have statistically lowered the Cronback alpha reliability coefficients. Tutor18 (e.g., tutors) had the lowest rating of all variables, with *M*=4 but conversely the variation was the highest at *SD*=0.6, which the authors conclude shows a few students may have used tutors.

From a statistical perspective, 3-5 students with greatly different item ratings (but not outliers) in a small sample size can impact the Cronbach alpha reliability estimates. Theoretically, the authors attribute this anomaly to the limited capability of the university to provide tutors for struggling students. The authors do not know for certain, as the authors did not capture that data, but the authors observed some students regularly received assistance from others outside of their team members. The authors did not observe any notable differences in culture or demographic characteristics so the authors assume the differences were programming aptitude, whereas, students with less ability in OOP sought the most economical available help from university resources. The authors think this statistical deviance in tutoring and library materials may be related because the tutors often spend time at the labs hosted inside the library and they make their services known through social media posts and emails to instructors. In conclusion, the authors recommend other scholars capture more details of student aptitude along with how much time is spent with tutors externally to their team members within the IS course.

Limitations and Recommendations

The limitation of this study, when considering the authors' goal was to sample an African university employing a cross-border American partnership strategy, was the small sample size of 84 cases. The authors do however admit other African universities ought to be sampled and the authors' research ought to be replicated to other African countries. The sample size limitation impacted the requirement in linear regression that there is a linear relationship between every independent factor and the dependent variable of student learning. This was not entirely met, especially for the excluded items of tutor and library, based on the authors' residual analysis although there were no outliers.

Most standard error (SE) estimates were relatively low for both factors in the final model (see table 3). Nonetheless, the SE for the vocational motivation factor was 0.219 before it was removed from the model (see table 2). The tolerance estimate for vocational-motivation was 0.213 which can be interpreted as almost 80% of this factor was somehow accounted by the other two factors to predict student learning. The high *VIF* of 4.691 corroborates this, revealing a higher than acceptable collinearity with other the other two factors, noting that was the first model and the authors did not keep that factor for the final solution. The authors may clearly see more evidence of this limitation in that design-content had a *VIF* of almost 6 before vocational-motivation was eliminated from the model (see table 2). In the two-factor final model, both tolerances were 80% and the *VIF*s were below 2 (see table 3).

The reader can see from the zero-order correlation of vocational-motivation at +0.535, this indicates it is related to student learning (as a bivariate coefficient, see table 2), but the other factors had higher coefficients, with design-content at -0.852 and active-engagement at +0.719. Nevertheless, this was a 29% effect size for vocational-motivation (the zero order R calculated as squared to r^2). The partial correlation of 0.142 accounts for how much variance vocational-motivation captured in shared effects of the other two factors to predict student learning. However, the partial correlation is calculated using residuals so statistically several relatively more extreme student ratings or learning scores in a small sample (but not outliers) could create this low partial correlation for the vocational-motivation factor. The semi-partial correlation eliminated the shared variance of the other factors to predict student learning, so at +0.052 it is understandably smaller than the partial correlation since the latter involved the shared variance of the two other factors (see Semi heading in table 2). This low semi-partial correlation indicates only a very small proportion of the variance in student learning can be accounted for by vocational-motivation. For a mathematical interpretation of this limitation, compare the low semi-partial correlation of vocational-motivation at +0.052 with a design-content semi-partial coefficient of -0.591 which is an order of magnitude larger, and an active-engagement semi-partial of +0.376 which is 7 times higher (see table 3).

The key limitation here was the two-factor model failed to account for seven items reported by students through the survey representing the vocational motivation factor so the authors must ask ourselves why that factor is not relevant to student learning. Did the authors waste their time hypothesizing this and capturing the data from busy students? The authors need to revisit the authors' theoretical research design and the authors sincerely invite other scholars to examine this phenomenon.

Although the authors felt confident that the authors could rationalize why students felt the IS course design was good but it negatively correlated with student learning (as being a western-country design), the authors would like to see more studies prove that through replications. Given the authors' online teaching experience, the authors felt the IS course design was a best practice so the authors hypothesize a longitudinal study would show acceptance by students over time, but the authors acknowledge more customization may be needed to accommodate sociocultural requirements of African employers. Nevertheless, this proposition needs to be scientifically investigated so the authors invite the authors' colleagues to help us do that.

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