Using Experiential Learning to Improve Student Attitude and Learning Quality in Software Engineering Education

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ABSTRACT

Experiential learning (EL) has great potential to transform students’ learning experiences. Few studies, however, have focused on the use of EL in computer science education. The purpose of this study was to examine students’ experiences with EL in computer science. Data were collected to examine the influence of EL on students’ attitudes and quality of learning. The antecedent variables included student involvement, learning expectancy, instructor impact, course structure, and prior experience. PLS-SEM with PLSc was used to test generated hypotheses. The findings indicated that student involvement positively correlated with attitudes and learning expectancy. Instructor impact is positively associated with student involvement, quality of learning, and attitudes. Prior experience positively correlated with learning expectancy. Finally, course structure positively moderated the relationship between student involvement and learning expectancy. It is concluded that EL is a promising pedagogy to improve student attitude and quality of learning in software engineering education.

KEYWORDS

Experiential Learning, Instructor Impact, Learning Expectancy, PLS-SEM, Quality of Learning, Software Engineering, Student Attitudes, Student Involvement, Student Perceptions

INTRODUCTION

Academic leaders in tertiary institutions have wrestled for over two decades with the persistent gap between software engineering education and industry needs. The conventional way of teaching students technical concepts in the classroom does not arm them with the skills that they need to succeed as professionals (Exter, 2014; Garousi, Giray, & Tuzun, 2019; Garousi, Giray, Tuzun, Catal, & Felderer, 2020; Hanna, Jaber, Almasalmeh, & Jaber, 2014; Kövesi & Csizmadia, 2016; Radermacher & Walia,
Most established universities that offer software engineering as part of their computer science programs offer courses designed to address the problem. Adopting experiential learning (EL) strategies could transform traditional pedagogy into a more learner-centered learning, thereby narrowing the skills gap in software engineering industry (Garousi et al., 2020; Holmes, Allen, & Craig, 2018; Ng & Huang, 2013). The EL pedagogy promises significant benefits for students, both academically and professionally, as it facilitates more profound learning, acquiring practical competencies, more engagement, appreciation of diversity, and exposure to professional networking opportunities (Coker & Porter, 2015; Holmes et al., 2018). Students who have taken an EL course find the overall experience positive - they appreciate the valuable mentorship gained from working on real projects with practical impact (Holmes et al., 2018).

Even though the EL pedagogy is transformative compared to the traditional pedagogy, students can often resist it (Chavan, 2011; Cornell, Johnson, & Jr, 2013; Hains & Smith, 2012; Lovelace & Brickman, 2013). Students are often reluctant to change from a traditional teacher-centered pedagogy that they know and trust (Bedawy, 2017; Hains & Smith, 2012). In other cases, students perceived the tasks involved as too complicated, or did not feel confident in their ability to complete the tasks, or were merely uncertain about how they would be assessed (Bedawy, 2017; Hains & Smith, 2012; Leveritt, Ball, & Desbrow, 2013; Lovelace & Brickman, 2013; Unda & Ramos, 2016). In some cases where EL was optional, some students preferred the traditional methods, which were perceived as more predictable (Brennan, 2014). Understanding the factors that lead students to resist EL could provide potential strategies to mitigate such resistance. Whether students have prior experience with a learner-centered course, or whether students perceive the instructor as knowledgeable, competent, and a good mentor could mitigate students’ resistance (Hains & Smith, 2012; Kahu, 2013; Redpath, 2012).

The EL pedagogy inherently incorporates students’ involvement as an essential ingredient for achieving learning outcomes (Kahu, 2013). In transitioning to EL, it makes sense to monitor students’ perceptions to confirm that attitudes are positive and that such a transformative pedagogy delivers a better quality of learning experience. In addition, quality of learning is a construct that reflects the degree of learning in terms of knowledge and skills gained and the extent to which students are satisfied with the learning process and experience (Thindwa, 2015).

The purpose of this study, therefore, was to examine the factors that would impact students’ attitude towards and learning quality of EL activities in a third-year software engineering course. Insights gleaned from the study could help identify promising instructional strategies to improve software engineering students’ preparation for future industry careers. The results could also be helpful to other software engineering programs considering introducing EL methods into their curriculum.

**LITERATURE REVIEW**

With the traditional teaching approach, often described as the teacher-centered, lecture-based approach, the instructor is actively involved in teaching while the learners are passive, receptive, and mainly listening. The EL approach is learner-centered and deliberately supports the compelling weaving together of educational learning, work, and personal development outcomes (Bavota, Lucia, Fasano, Oliveto, & Zottoli, 2012; Dragoumanos et al., 2017; Ellis et al., 2015; Holmes et al., 2018; Krutz et al., 2014; Stroulia et al., 2011). The preponderance of evidence in social science research indicates that EL not only improves student’s engagement and student’s overall performance but narrows the gap between the theoretical concepts taught in the classroom and the skills needed for graduates to succeed once they join the professional workforce (Accenture, 2018; Garousi et al., 2020; Hanna et al., 2014; Ng & Huang, 2013; Radermacher & Walia, 2013; Tuzun et al., 2018). Therefore, program designers in many tertiary institutions have explored various strategies to incorporate EL into their programs.
Student involvement is a critical ingredient for learning. Involvement is a measure of the degree of attention, time, and effort devoted by students to accomplishing learning activities both inside and outside of the classroom (Groccia, 2018; Kuh, 2013; Rangvid, 2018; Woods, Price, & Crosby, 2019). According to Rangvid (2018), student involvement is a multidimensional construct that captures the degree of engagement, connectedness, commitment, and motivation to learn. Students must engage with the learning process on all levels. Various technologies and active learning methods, mentoring and coaching, can be deployed to improve student involvement and quality of learning (Bhati & Song, 2019; Lietaert, Roorda, Laevers, Verschueren, & De Fraine, 2015).

Variables that are relevant to involvement are also included in the study. The Unified Theory of Acceptance and Use of Technology (UTAUT) is often used to study attitude, intention, and behaviour in technology adoption (Alshare & Lane, 2011; Fauzi, Ali, & Amirudin, 2019; Sair & Danish, 2018). In addition, Expectancy Theory is often used to explain how people’s anticipation of the desired outcome influences their choices and performance. In this study, learning expectancy relates to a student’s expectation that their learning activities’ involvement improves their learning quality and performance (Alshare & Lane, 2011; Shweiki et al., 2015; Unda & Ramos, 2016). Learning expectancy reflects the notion of perceived ease of use and EL pedagogy’s perceived usefulness (Sair & Danish, 2018). The strength of the association between student involvement and the desired outcome is a measure of motivation reflected in a student’s attitude. The introduction of EL was expected to improve students’ participation and positively influence students’ attitudes toward learning (Coker, Heiser, Taylor, & Book, 2017; Fauzi et al., 2019; Leal-Rodríguez & Albert-Morant, 2019; Shweiki et al., 2015). Hence, the following hypotheses were tested, which are also depicted in Figure 1:

Hypothesis 1 (H1): Student involvement in EL positively impacts attitude.
Hypothesis 2 (H2): Student involvement in EL positively impacts the perceived quality of learning.
Hypothesis 3 (H3): Student involvement in EL positively impacts perceived learning expectancy.
Hypothesis 4 (H4): Learning expectancy positively impacts perceived quality of learning.
Hypothesis 5 (H5): Learning expectancy positively impacts attitude.

EL is a learner-centered pedagogy that is informed by the constructivist approach (Allsop, 2016; Bada, 2015; Bose, 2018; Capacho, 2016; Jha, 2017; Kolb & Kolb, 2018; Passarelli & Kolb, 2011; Raihan & Lock, 2012). Through their efforts, the learner constructs knowledge, learning-by-doing as they partake in solving problems, either individually or collaboratively, and critically reflecting on any insights that emerge. The instructor’s role is primarily as a coach and mentor. In this study, the instructor’s impact was reflected by the degree to which the instructor was perceived as knowledgeable and effective in guiding and facilitating student learning. The instructor was expected to influence students’ involvement, attitudes, and quality of learning (Cooper, Ashley, & Brownell, 2017; Exter, 2014; Fauzi et al., 2019; Fielding-Wells, O’Brien, & Makar, 2017; Leveritt et al., 2013; Schindler, Burkholder, Morad, & Marsh, 2017; Shweiki et al., 2015; Unda & Ramos, 2016). Student’s prior experience and the course structure could also influence participation. As such, the following hypotheses were also tested, and were depicted in Figure 1:

Hypothesis 6 (H6): Perceived instructor impact positively impacts student involvement.
Hypothesis 7 (H7): Perceived instructor impact positively impacts the perceived quality of learning.
Hypothesis 8 (H8): Perceived instructor impact positively impacts attitude.
Hypothesis 9 (H9): Perceived impact of course structure positively impacts student involvement.
Hypothesis 10 (H10): Perceived impact of course structure positively impacts perceived learning expectancy.
Hypothesis 11 (H11): Degree of prior experience positively impacts student involvement.
Hypothesis 12 (H12): Degree of prior experience positively impacts perceived learning expectancy.
Hypothesis 13 (H13): Degree of prior experience positively impacts perceived learning quality.
DESIGN OF EL IN SOFTWARE ENGINEERING

EL in a software engineering course usually implies incorporating various learning-by-doing activities with an emphasis on enriching the students’ learning experience in either the engineering or project management aspects or both. These activities include: working on real-world software development projects to gain a deeper understanding of the complexities of the processes involved or the tools and the techniques necessary for developing quality software, and provide an opportunity to develop practical skills as well as real-world exposure to professional collaboration (Dragoumanos, Kakarountas, & Fourou, 2017; D’Souza & Rodrigues, 2015; Garousi et al., 2020; Gray & Christov, 2017a, 2017b; Hanna et al., 2014; Krutz, Malachowsky, & Reichlmayr, 2014; Ng & Huang, 2013; Regehr, 2018). Besides, students gain from ongoing mentoring, which is an opportunity to actively reflect on what they are working on, analyze, process, and apply any learnings to improve their deliverables. To get the best out of the experience, students must be actively involved.

Participation is an essential aspect of any course and an even more critical part of an EL course, as was the case in this study. As listed in Table 12 in Appendix A, the structure of the course sessions included two components. Each week’s first 90 minutes session was a lecture focused on the theoretical foundations and principles of software engineering. The second 90 minutes session concentrated on EL activities aimed at building on any theoretical foundations earlier introduced. The activities included expectations discussions, tools and environment setup exercises, hands-on practical exercises, a team project, unpacking discussion sessions, and EL assessments. The course syllabus, lecture slides, and supporting materials were organized and provided via a standard Learning Management System (LMS). The course materials and the lectures offered an organized learning experience and as much constructive aligned as possible so that students could readily match expected accomplishments with the corresponding assessment (Lackëus & Middleton, 2018). Also, independent student-centered learning was supported using a variety of media. The EL sessions involved students working in teams to tackle specific programming challenges, and the instructor acted primarily as a mentor or guide during those sessions. The instructor offered periodic or on-demand unpacking discussion sessions during which individual students or teams met to go over any aspects of the EL activities or even the assessments. The unpacking sessions were completely ungraded, outside of the class sessions, and many students took advantage of these to clarify any areas of ambiguity in the exercises or course materials. Additionally, students used these sessions to explore creative problem-solving ideas.
METHODOLOGY

In this study, a quantitative research design was adopted to investigate EL pedagogy’s impact on students’ attitudes and learning experience. A quantitative approach is useful when exploring the factors that influence an outcome (Creswell, 2013). A questionnaire was designed, pretested on a separate sample of 15 undergraduate software engineering students; minor modifications were made to improve some question-statements perceived as ambiguous before it was administered to the participants via SurveyGizmo in December 2019.

Participants

The participants in this study were from four cohorts of undergraduate students majoring in software engineering at the American University of Nigeria (“AUN”), Yola, Nigeria. All participants had completed a mandatory third-year software engineering course in computer science unique in Nigeria because AUN programs emphasize critical thinking and problem-solving. The experiential learning pedagogy had been adopted for the course since Spring 2018 and led by the same instructor.

Of the 101 students who had completed the course since Spring 2018 and were invited to participate in the online survey, 76 students (75%) responded, nine responses were incomplete and eliminated, resulting in a total valid sample of 67 respondents, a 66% valid response rate. A response rate of 50% is considered acceptable for online student learning surveys (Liu & Wronski, 2018; Petrovčič, Petrič, & Lozar Manfreda, 2016; Saleh & Bista, 2017). The respondents’ demographic breakdown was male (78%) and under 25 years (91%).

Measures and Procedures

The main part of the questionnaire was dedicated to information on students’ perceptions of their learning experience. The instructor impact, course structure, and prior experience indicators were adapted from a previous study on student learning experiences (Alshare & Lane, 2011). The EL indicators, which included attitude, student involvement, learning expectancy, and learning quality, were adapted from a previous study on the assessment of EL (De Zan et al., 2015). The participants were asked to respond to question-statements based on a 5-point Likert scale ranging from strongly disagree (1) to strongly agree (5).

Analysis Methods

A variety of tools and techniques was used to conduct the data analysis. Confirmatory factor analysis (CFA), using parallel analysis with the oblique rotation method, was conducted. The CFA was used to test that the measured perception indicators were consistent with the latent constructs in the developed study model (Alshare & Lane, 2011; Marsh, Guo, Dicke, Parker, & Craven, 2020; Marsh, Morin, Parker, & Kaur, 2014; R Core Team, 2020; Revelle, 2020; RStudio, 2019). The oblique rotation method or “oblimin” was used instead of the traditional “varimax” because of expected correlations between the indicators and factors (Tóth-Király, Bőthe, Rigó, & Orosz, 2017). The model goodness of fit (GoF) and factor loadings were checked against generally recommended guidelines, and some non-significant factors were dropped (Dvork, 2017; Kock, 2019; Kock, Avison, & Malaut, 2017; Thoma et al., 2018). The model fit indices from the CFA, listed in Table 1, indicated that the model was acceptable for the instructor impact (II) and course structure (CS) factors (Xia & Yang, 2019). For the student attitude (SA), student involvement (SI), learning expectancy (LE), and quality of learning (QL) factors, the Tucker-Lewis index (TLI) was 0.764, which is barely acceptable, indicating that the model could be improved. However, because the other indices were acceptable and with the root mean square error of approximation (RMSEA) close to 0.60 (Xia & Yang, 2019), the model was used with no further improvements.

A partial least squares structural equation modeling (PLS-SEM) analysis of the study path models was conducted with latent variables based on the measured indicators, as listed in Table 2. All latent
variables were measured reflectively through multiple indicators except the prior experience indicator. WarpPLS 6.0 (Kock, 2017) was used to conduct a robust nonlinear path analysis because it supports the newer consistent PLS (PLSc) technique (Dijkstra & Henseler, 2015; Kock, 2019). The general WarpPLS model analysis settings selected included the “Factor-Based PLS Type CFM3” option for the outer model analysis algorithm because it relies on Dijkstra’s PLSc technique (Dijkstra & Henseler, 2015). The “Warp3” algorithm was selected for the inner model since it caters to nonlinearity in the latent variable relationships (Kock, 2019). Finally, the “Stable3” resampling method was selected as it generates more stable path coefficients and reliable p-values when the sample size is small (N<100) (Kock, 2011, 2019).

We relied on the inverse square root method to estimate and validate the study sample size (Kock & Hadaya, 2018). The analysis confirmed that the sample (N=67) would result in statistical power equal to or greater than 80%, hence acceptable (Benitez, Henseler, Castillo, & Schuberth, 2019; Kock & Hadaya, 2018). Based on expected statistical power estimates, some model paths with low β coefficients (β<0.30) (Kock et al., 2017) and non-significant paths were removed (Benitez et al., 2019; Hair, Hult, Ringle, & Sarstedt, 2016; Kock et al., 2017; Kock & Hadaya, 2018). The final estimated model, in Figure 2, was obtained after dropping all indicators with non-significant loadings (Kock, 2011, 2019), which also corresponded to those indicators with communalities lower than 0.30 in Table 1.

RESULTS

The final estimated model’s assessment in Figure 2 included its overall GoF, quality, or validity of the measurement and structural models, as listed in Table 3. The Tenenhaus GoF, a measure of the model’s explanatory power, was 0.553, indicating that the model had large explanatory power (Kock, 2019). For a good model, the APC, ARS, and AARS indices should be significant at the 5% level (Kock, 2019). Table 3 shows that all three criteria were met. Similarly, both the AVIF and AFVIF indices,
which are vertical and full collinearity measures, met the tighter recommended threshold (Kock, 2019). The SPR, which is a measure of the extent to which the model is free of Sympon’s paradox, was 1.0, and the related RSCR was 1.0. The SSR, which is a measure of statistical suppression, was also 1.0. Finally, the NLBCDR, which is a measure of the extent to which the bivariate nonlinear coefficients of association support the hypothesized directions of the model’s causal links, was 1.0. Therefore, the SPR, RSCR, SSR, NLBCDR were acceptable.

The latent variables’ composite reliabilities, which is a measure of the correlation between each latent variable and its construct indicator scores, were estimated. Composite reliability is acceptable if the latent variables’ Dijkstra’s rho_a is above the recommended threshold of 0.707 (Benitez et al., 2019; Kock, 2014, 2019). Table 4 shows that the composite reliabilities of all latent constructs were above the acceptable threshold, and the construct indicator scores were considered reliable. Convergent validity, a measure of the extent to which the indicators associated with a latent variable measure the same construct, was assessed for the latent variables. Convergent validity is acceptable
if the p-values associated with the latent variable’s indicator loadings are significant at the 5% level and each of its indicator loadings is equal to or greater than 0.50 (Benitez et al., 2019; Kock, 2014, 2019). Additionally, the average variances extracted (AVE) for each latent variable should be greater than 0.50 (Benitez et al., 2019; Kock, 2019). As seen in Table 4, the convergent reliabilities of all the latent variables were acceptable.

Discriminant validity, a measure of the degree to which a latent variable construct is sufficiently distinct from other latent variables, was also estimated (Hair et al., 2016). It is acceptable if the AVE’s square roots for each latent variable are higher than any of its correlations between that latent variable and others (Benitez et al., 2019; Kock, 2019; Kock & Lynn, 2012). The entries on the diagonal of Table 5 were compared with the entries in the row to the left of and the column below them (Kock, 2019; Kock & Lynn, 2012). The diagonals’ numbers should be higher if there is acceptable discriminant validity (Kock, 2019; Kock & Lynn, 2012). All latent variables had acceptable discriminant validity except the Attitude variable, indicating a possible collinearity presence in the model (Kock, 2019; Kock & Lynn, 2012). Variance inflation factor (VIF), a measure of vertical collinearity or collinearity among predictor latent variables in blocks where two or more predictors point at one criterion latent variable are involved, was also estimated. The rule of thumb is that a VIF with a value 3.3 or lower, or more relaxed lower than 5.0, indicates no vertical collinearity in the latent variable block (Kock, 2019; Kock & Lynn, 2012). As seen in Table 6, all VIFs were below the expected threshold, suggesting no vertical collinearity in the model.

Another type of collinearity, lateral collinearity, a measure of collinearity among indicators of endogenous latent variables, was also estimated. The indicator VIFs, weights, and loadings were examined based on the criteria for acceptable VIFs stated earlier (Kock, 2019; Kock & Lynn, 2012). Table 4 shows that the measured indicator VIFs are all below the tighter threshold of 3.3. Additionally, almost all of the indicator weights were significant, except some of the Attitude, CrsStruc, and InstrImp indicators. Indicators with non-significant weights and weak effect size (ES) (ES<0.02) (Benitez et al., 2019; Kock, 2019; Kock & Lynn, 2012), and if doing so would not compromise construct validity (Kock, 2019; Kock & Lynn, 2012). A full multicollinearity test was also conducted, and as seen in Table 7, all the latent variables met the more relaxed threshold (VIF<5.0). All the indicator loadings in Table 4 were significant, and that all indicator ES values were above the recommended threshold. Therefore, all the suspect indicators were retained to preserve construct validity (Benitez et al., 2019; Kock, 2019; Kock & Lynn, 2012), despite the potential presence of lateral collinearity in the model.

Correlation among the latent variable error terms can help establish whether there is a possible existence of hidden confounder(s) or a third variable not represented or captured by the model (Kock, 2019). To rule out any hidden confounders is none of the correlations should be significant at the 5% level, and the associated VIFs should meet the recommended threshold (Kock, 2019). Table 8 shows
Table 4. Measurement model evaluation

| Construct/Indicator Code | Dijkstra's α | Cronbach's α | AVE   | VIF | Weight | Loading | Effect Size |
|--------------------------|--------------|--------------|-------|-----|--------|---------|-------------|
| Attitude                 | 0.866        | 0.861        | 0.660 |     |        |         |             |
| SP10                     | 1.603        | 0.152*       | 0.566*** | 0.092 |        |         |             |
| SP12                     | 1.499        | 0.089        | 0.593*** | 0.053 |        |         |             |
| SP13                     | 1.900        | 0.087        | 0.611*** | 0.053 |        |         |             |
| SP14                     | 1.779        | 0.191*       | 0.556*** | 0.106 |        |         |             |
| SP20                     | 1.697        | 0.216*       | 0.750*** | 0.162 |        |         |             |
| SP21                     | 2.013        | 0.193*       | 0.659*** | 0.128 |        |         |             |
| SP38                     | 2.093        | 0.057        | 0.745*** | 0.050 |        |         |             |
| SP40                     | 2.493        | 0.192*       | 0.761*** | 0.146 |        |         |             |
| CrsStruc                 | 0.790        | 0.787        | 0.744 |     |        |         |             |
| SP31                     | 1.785        | 0.226*       | 0.758*** | 0.347 |        |         |             |
| SP32                     | 1.471        | 0.096        | 0.706*** | 0.114 |        |         |             |
| SP33                     | 1.844        | 0.405***     | 0.768*** | 0.203 |        |         |             |
| Instrimp                 | 0.823        | 0.814        | 0.687 |     |        |         |             |
| SP26                     | 1.497        | 0.181*       | 0.590*** | 0.107 |        |         |             |
| SP27                     | 2.185        | 0.383***     | 0.771*** | 0.299 |        |         |             |
| SP28                     | 1.810        | 0.092        | 0.614*** | 0.057 |        |         |             |
| SP29                     | 1.745        | 0.332**      | 0.752*** | 0.250 |        |         |             |
| SP30                     | 1.555        | 0.034        | 0.690*** | 0.023 |        |         |             |
| Exptancy                 | 0.815        | 0.813        | 0.718 |     |        |         |             |
| SP33                     | 1.672        | 0.226*       | 0.704*** | 0.159 |        |         |             |
| SP35                     | 1.920        | 0.096        | 0.687*** | 0.056 |        |         |             |
| SP36                     | 2.504        | 0.405***     | 0.856*** | 0.265 |        |         |             |
| SP44                     | 1.517        | 0.243*       | 0.816*** | 0.198 |        |         |             |
| ExpLearn                 | 0.845        | 0.839        | 0.749 |     |        |         |             |
| SP15                     | 1.464        | 0.224*       | 0.754*** | 0.169 |        |         |             |
| SP18                     | 2.545        | 0.257*       | 0.675*** | 0.173 |        |         |             |
| SP19                     | 3.004        | 0.241*       | 0.672*** | 0.162 |        |         |             |
| SP22                     | 1.875        | 0.388*       | 0.875*** | 0.340 |        |         |             |
| PriorExp                 | 1.000        | 1.000        |       |     | -      | 1.000*** | 1.000*** | 1.000 |
| QualLearn                | 0.870        | 0.869        | 0.789 |     |        |         |             |
| SP41                     | 2.666        | 0.216*       | 0.802*** | 0.173 |        |         |             |
| SP42                     | 1.843        | 0.204*       | 0.780*** | 0.159 |        |         |             |
| SP43                     | 1.903        | 0.357***     | 0.827*** | 0.295 |        |         |             |
| SP45                     | 2.625        | 0.24*        | 0.746*** | 0.179 |        |         |             |
| CrsStruc*ExpLearn        | 0.890        | 0.884        | 0.621 |     |        |         |             |
| SP31*SP15                | 2.922        | 0.172*       | 0.414*** | 0.071 |        |         |             |
| SP31*SP18                | 4.657        | -0.052       | 0.674*** | 0.042 |        |         |             |
| SP31*SP19                | 10.881       | 0.131        | 0.705*** | 0.093 |        |         |             |
| SP31*SP22                | 9.760        | 0.159*       | 0.629*** | 0.100 |        |         |             |
| SP32*SP15                | 2.555        | 0.101        | 0.490*** | 0.050 |        |         |             |
| SP32*SP18                | 2.590        | 0.150*       | 0.592*** | 0.089 |        |         |             |
| SP32*SP19                | 6.351        | 0.178*       | 0.588*** | 0.105 |        |         |             |
| SP32*SP22                | 5.775        | -0.046       | 0.509*** | 0.023 |        |         |             |
| SP33*SP15                | 3.742        | 0.047        | 0.559*** | 0.036 |        |         |             |
| SP32*SP18                | 5.220        | 0.083        | 0.688*** | 0.057 |        |         |             |
| SP32*SP19                | 7.311        | 0.129        | 0.817*** | 0.106 |        |         |             |
| SP33*SP22                | 6.281        | 0.294*       | 0.683*** | 0.201 |        |         |             |
Table 5. Latent variable correlations and square-roots of AVEs

|                | InstrImp | ExpLearn | Exptancy | QualLearn | Attitude | CrsStruc | PriorExp | CrsStruc*ExpLearn |
|----------------|----------|----------|----------|-----------|----------|----------|----------|-------------------|
| InstrImp       |          |          |          |           |          |          |          | (0.687)           |
| ExpLearn       | 0.359    |          |          |           |          |          |          | (0.749)           |
| Exptancy       | 0.466    | 0.533    |          |           |          |          |          | (0.718)           |
| QualLearn      | 0.742    | 0.556    | 0.764    |           |          |          |          | (0.789)           |
| Attitude       | 0.760    | 0.569    | 0.624    | 0.786     |          |          |          | (0.660)           |
| CrsStruc       | 0.710    | 0.287    | 0.451    | 0.807     | 0.623    |          |          | (0.744)           |
| PriorExp       | 0.057    | -0.192   | 0.222    | 0.217     | 0.011    | 0.056    |          | 1.000             |
| CrsStruc*ExpLearn | 0.033  | 0.215    | 0.108    | 0.079     | 0.042    | 0.045    | -0.178   | (0.621)           |

Note. Square roots of AVEs are shown on the diagonal, within parentheses.

Table 6. Vertical collinearity estimates

|                | InstrImp | ExpLearn | Exptancy | QualLearn | Attitude | CrsStruc | PriorExp | CrsStruc*ExpLearn |
|----------------|----------|----------|----------|-----------|----------|----------|----------|-------------------|
| Exptancy       |          | 1.319    |          |           |          |          | 1.030    | 1.351             |
| QualLearn      | 1.279    |          |          |           |          |          |          |                   |
| Attitude       | 1.190    |          |          |           |          |          |          |                   |

Note. VIFs for each predictor (column) with reference to a criterion latent variable (rows).

Table 7. Estimated latent variable coefficients

| Variable       | R-squared | Adj. R-squared | Cronbach’s α | Dijkstra’s p | AVE | Full Collin. VIF | Ω-squared |
|----------------|-----------|----------------|---------------|-------------|-----|-----------------|----------|
| InstrImp       | 0.814     | 0.823          | 0.814         | 3.652       |     |                 |          |
| ExpLearn       | 0.142     | 0.129          | 0.839         | 0.845       | 0.639 | 2.034          | 0.224    |
| Exptancy       | 0.523     | 0.501          | 0.813         | 0.815       | 0.813 | 2.713          | 0.566    |
| QualLearn      | 0.786     | 0.780          | 0.869         | 0.870       | 0.869 | 5.025          | 0.791    |
| Attitude       | 0.703     | 0.693          | 0.861         | 0.865       | 0.861 | 3.978          | 0.713    |
| CrsStruc       | 0.787     | 0.790          | 0.787         | 0.787       | 0.787 | 2.143          |          |
| PriorExp       | 1.000     | 1.000          | 1.000         | 1.000       | 1.000 | 1.358          |          |
| CrsStruc*ExpLearn | 0.884  | 0.890          | 0.884         | 1.095       |     |                 |          |

Table 8. Correlations among latent variable error terms, associated VIFs (on diagonal)

|                | InstrImp | ExpLearn | Exptancy | QualLearn | Attitude | CrsStruc | PriorExp |
|----------------|----------|----------|----------|-----------|----------|----------|----------|
| InstrImp       |          |          |          |           |          |          |          |
| ExpLearn       | (1.041)  |          |          |           |          |          |          |
| Exptancy       | -0.044   | (1.070)  |          |           |          |          |          |
| QualLearn      | 0.194    | -0.082   | (1.102)  |           |          |          |          |
| Attitude       | 0.010    | 0.220    | 0.203    | (1.109)   |          |          |          |
| CrsStruc       |          |          |          |           |          |          |          |
| PriorExp       |          |          |          |           |          |          |          |

Note: †p<0.10, *p < 0.05 for the error term correlations.
that none of the error term correlations were significant, and all the VIFs met the recommended threshold, suggesting that there were no evident hidden confounders in the model.

The Stone-Geisser or Q-squared coefficient is a non-parametric measure of each predictor latent variable’s predictive validity or relevance through an endogenous criterion latent variable in a latent variable block (Kock, 2019). Acceptable predictive validity should be greater than zero (Kock, 2019). Table 7 shows that all the relevant latent variable blocks met the criteria, indicating acceptable model predictive validity.

Evaluating the Path Coefficients and Hypotheses

The estimated model path coefficients generated by WarpPLS are standardized regression coefficients. Each path coefficient indicates that if the independent latent variable changes by one standard unit, when all other explanatory constructs are kept constant, then the dependent latent variable can be expected to change by the coefficient amount (Benitez et al., 2019; Kock, 2019). Additionally, the effect size of any significant relationship between constructs should be investigated to establish its practical significance (Benitez et al., 2019; Kock, 2019; Kock & Hadaya, 2018; Marsh et al., 2020, 2014). The effect size is a measure of the magnitude of an effect, independent of sample size. The effect size should range from 0.020 to 0.150 (weak effect), 0.150 to 0.350 (medium), or equal to or larger than 0.350 (large) (Benitez et al., 2019; Hair et al., 2016; Kock, 2019; Kock & Hadaya, 2018; Marsh et al., 2020, 2014; Tóth-Király et al., 2017). Table 9 shows that the estimated model’s effect sizes ranged from 0.142 (weak) to 0.465 (large).

Furthermore, the coefficient of determination (R-squared) is often used in ordinary least square regression to indicate the proportion of variance in the dependent construct explained by the model (Benitez et al., 2019; Kock, 2019; Kock & Lynn, 2012). It is a measure of the model’s in-sample predictive power in PLS-SEM (Benitez et al., 2019; Kock, 2019; Marsh et al., 2020). Figure 2 and Table 7 show that the construct R-squared values ranged from 0.142 (ExpLearn) to 0.703 (Attitude). The R-squared value for the student involvement construct was very small. Still, it was impossible to establish whether there was cause for concern because other comparable empirical studies on EL were not found.

Table 9. Path coefficients and effect sizes

| Relationship | Coefficient | Effect Size |
|--------------|-------------|-------------|
| Students’ perceived involvement -> Students’ attitudes (H1) | 0.380*** | 0.237 |
| Students’ perceived involvement -> Perceived quality of learning (H2) | 0.359*** | 0.196 |
| Students’ perceived involvement -> Students’ learning expectancy (H3) | 0.527*** | 0.402 |
| Students’ learning expectancy -> Students’ attitudes (H5) | 0.377*** | 0.142 |
| Students’ perceived level of instructor impact -> Students’ perceived involvement (H6) | 0.509*** | 0.384 |
| Students’ perceived level of instructor impact -> Perceived quality of learning (H7) | 0.610*** | 0.485 |
| Students’ perceived impact of course structure -> Students’ perceived involvement (H9) | 0.344*** | 0.147 |
| Students’ perceived impact of course structure -> Perceived quality of learning (H12) | 0.324** | 0.181 |

Note: †p<0.10, *p < 0.05, **p < 0.01, ***p < 0.001, one-tailed test.
As listed in Table 3, the model explained 53% (AARS=52.6) of the variation in the study outcomes of quality of learning and attitudes. Figure 2 and Table 7 also show that the instructor impact and learning expectancy explained 78.6% of the variation in learning quality. Similarly, instructor impact and student involvement explained 70.3% of the variation in attitudes and only 14.2% for student involvement. Finally, student involvement and prior experience explained 52.3% of the variation in learning expectancy.

All the path coefficients in the final model were significant at the 5% level, as seen in Figure 2 and Table 9. Figure 2 and Table 11 show that several of the hypothesized relationships were significant at the 5% level and supported. Instructor impact positively correlated with quality of learning ($\beta=0.580$, $P<0.001$), student involvement ($\beta=0.377$, $P<0.001$), and attitudes ($\beta=0.754$, $P<0.001$). Student involvement positively correlated with attitude ($\beta=0.380$, $P<0.001$), learning expectancy ($\beta=0.359$, $P<0.001$), but only indirectly with quality of learning ($\beta=0.189$, $P<0.011$) through learning expectancy. Similarly, learning expectancy positively correlated with quality of learning ($\beta=0.527$, $P<0.001$) but not attitude. Instructor impact positively correlated with student involvement ($\beta=0.377$, $P<0.001$), quality of learning ($\beta=0.509$, $P<0.001$), and attitude ($\beta=0.610$, $P<0.001$). Instructor impact also positively correlated indirectly with attitudes ($\beta=0.144$, $P<0.043$), learning expectancy ($\beta=0.136$, $P<0.053$), but not quality of learning ($\beta=0.071$, $P<0.152$). Therefore, any indirect effect on the quality of learning was solely because of student involvement. Prior experience positively correlated

### Table 10. Estimated total effects with associated path coefficients and (number of paths, effect size)

| Hypothesis                           | $\beta$  | $P$     |
|--------------------------------------|----------|---------|
| Students' perceived involvement $\rightarrow$ Students' attitudes ($H1$) | $0.580$  | $<0.001$|
| Students' perceived involvement $\rightarrow$ Perceived quality of learning ($H2$) | $0.377$  | $<0.001$|
| Students' perceived involvement $\rightarrow$ Students' learning expectancy ($H3$) | $0.359$  | $<0.001$|
| Students' learning expectancy $\rightarrow$ Perceived quality of learning ($H4$) | $0.189$  | $<0.011$|
| Students' learning expectancy $\rightarrow$ Students' attitudes ($H5$) | $0.527$  | $<0.001$|
| Students' perceived level of instructor impact $\rightarrow$ Students' perceived involvement ($H6$) | $0.380$  | $<0.001$|
| Students' perceived level of course structure $\rightarrow$ Students' perceived quality of learning ($H7$) | $0.359$  | $<0.001$|
| Students' perceived level of course structure $\rightarrow$ Students' perceived quality of expectancy ($H10$) | $0.189$  | $<0.011$|
| Students' degree of prior experience $\rightarrow$ Students' perceived involvement ($H11$) | $0.509$  | $<0.001$|
| Students' degree of prior experience $\rightarrow$ Perceived quality of learning ($H13$) | $0.136$  | $<0.053$|
| Students' perceived impact of course structure $\rightarrow$ Students' learning expectancy (moderating) | $0.144$  | $<0.043$|

**Note:** $\dagger p<0.10$, $^* p < 0.05$, $^{**} p < 0.01$, $^{***} p < 0.001$.

### Table 11. Summary evaluation of hypotheses

| Hypothesis | Supported |
|------------|-----------|
| Students' perceived involvement $\rightarrow$ Students' attitudes ($H1$) | Yes |
| Students' perceived involvement $\rightarrow$ Perceived quality of learning ($H2$) | No |
| Students' perceived involvement $\rightarrow$ Students' learning expectancy ($H3$) | Yes |
| Students' learning expectancy $\rightarrow$ Perceived quality of learning ($H4$) | Yes |
| Students' learning expectancy $\rightarrow$ Students' attitudes ($H5$) | No |
| Students' perceived level of instructor impact $\rightarrow$ Students' perceived involvement ($H6$) | Yes |
| Students' perceived level of course structure $\rightarrow$ Students' perceived quality of learning ($H7$) | No |
| Students' perceived level of course structure $\rightarrow$ Students' perceived quality of expectancy ($H10$) | No |
| Students' degree of prior experience $\rightarrow$ Students' perceived involvement ($H11$) | No |
| Students' degree of prior experience $\rightarrow$ Perceived quality of learning ($H13$) | No |
| Students' perceived impact of course structure $\rightarrow$ Students' learning expectancy (moderating) | Yes |
with learning expectancy (β=0.344, P<0.001) but nothing else. Finally, course structure positively moderated the student involvement relationship with learning expectancy (β=0.324, P<0.002).

Concerning the association involving attitudes, instructor impact had a much stronger effect than student involvement based on the path coefficients, as seen in Figure 2 and Table 10. For the association with quality of learning, instructor impact, and learning expectancy were almost equally impactful. For the association with learning expectancy, both student involvement and prior experience had an almost equal impact. Interestingly, instructor impact had a relatively moderate effect on student involvement. Given the relatively small coefficient of determination on student involvement (R-squared= 0.142), this may indicate that additional factors, not accounted for, influence student involvement. However, no comparable empirical studies could be found to make a considered assessment as to whether there was cause for concern.

**DISCUSSION**

As shown in the above section, a statistically significant SEM was fitted to survey the data, demonstrating that student involvement in EL was positively associated with attitude and quality of learning in an undergraduate software engineering course (n=67). The final model had a GoF of 55% and good explanatory power (R²=0.526, P<0.05). In the model, instructor impact had the most significant overall influence on student attitude with a large effect size (ES=0.575). The instructor impact also significantly influenced the quality of learning with a large effect size (ES=0.438). The instructor impact had a significant influence on student involvement with a small effect size (ES=0.142). Student involvement had a significant influence on learning expectancy with a small effect size (ES=0.196). Student involvement also had a significant impact on student attitude with a moderate effect size (ES=0.237). Finally, learning expectancy significantly influenced the quality of learning with a large effect size (ES=0.402). These results corroborated other findings in the extant literature, which suggest that student attitude, involvement, and learning experience improve when the EL pedagogy is adopted (Lackéus & Middleton, 2018).

Interestingly, the course structure had a significant influence only as a moderator in the relationship between student involvement and learning expectancy (β=0.324, P<0.05), with a moderate effect size (ES=0.181). This moderator represented the conditional association of course structure on learning expectancy and could indicate that a proportion of the students felt that the course design helped them learn, potentially reducing complexity or providing an easy to follow roadmap. However, another factor that could also account for this result was prior experience, which had a significant influence on learning expectancy (β=0.344, P<0.05) with a moderate effect size (ES=0.147). Coincidently, prior experience did not significantly associate with other hypothesized factors such as student involvement or quality of learning. There were also mixed findings in the literature concerning the impact of prior experience on EL perceptions. Some researchers claimed that prior experience could influence learning expectancy, whereas others asserted that there could be moderating relationships from prior experience to other factors, including learning expectancy (Cooper et al., 2017; Fauzi et al., 2019; Fielding-Wells et al., 2017; Shweiki et al., 2015; Unda & Ramos, 2016). In this study, prior experience could have been preconditioned by student exposure with the same instructor from other computer science courses or the instructors being well-recognized and highly regarded across the university. Surprisingly, student involvement had only a small indirect effect on the quality of learning (β=0.189, P<0.05) with a weak effect size (ES=0.101). The lack of a direct relationship between student involvement and quality of learning could reflect some confusion within the survey items where quality of learning may have been perceived as driven by the instructor and thus associated with the instructor factor instead. Nevertheless, this finding was consistent with the a priori literature in as far as student involvement should relate to student attitude and learning expectancy but not directly to learning quality (Alkan, 2016; Armbruster et al., 2009; Bruegge et al., 2015). Other similar future
studies with larger samples in other higher education institutions may provide additional evidence or confirmation of the findings of this study.

CONCLUSION

A review of the relevant literature revealed that EL is a transformative pedagogy that promises student engagement and performance improvements. However, few empirical studies have examined how computer science students perceive learner-centered pedagogy in higher education institutions. In this study, EL was empirically examined within the context of an undergraduate soft engineering course. A statistically robust set of techniques was applied to test the hypotheses, using CFA and then PLS-SEM with consistent partial least squares (PLSc) for the study model’s path analysis. As revealed and confirmed by the results, EL is a promising instructional technique that has the great potential to enhance student attitude and learning quality in software engineering education.

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APPENDIX A. TABLES 12 AND 13

Table 12 shows the breakdown of the experiential learning activities in the introduction to software engineering course, and Table 13 shows the perception indicators.

Table 12. Experiential learning activities in the software engineering course

| Activity Categories | Description |
|---------------------|-------------|
| Supervisory Discussion | A critical component of participation. The first session in the first week of the course in which students obviously discuss their expectations relating to the course with the instructor. The discussions usually broadly include student interests in the course, reasons for taking the course, prior exposure to or experience with. Experiential learning activities of each student bring to the course in terms of prior knowledge and/or software development or learning experiences which students build on prior learning in the course and how each student expects the course to benefit them. The instructor also participates in the discussions by answering any questions, particularly about experiential learning, explaining the assessment methodology and how to view and assess their own experiences on real-world projects in the industry. |
| Tools & Environment Setup | This includes the preparatory activities associated with the playing field to ensure that all students acquire the necessary knowledge to work independently and contribute to teamwork throughout the course. This component kicks off in the second week of the course and is usually completed by the second week. The instructor’s teaching and guidance is critical in providing meaningful real-world justification for the activities and ensuring all students actively participate in the activities and can follow the documented notes and activity steps. The preparatory tools and activities to support hands-on exercises include: preparing and setting up each student’s DSS for software development (i.e., configuring environment variables), installing and configuring Java, SSH, and MySQL. Additionally, Java development, Python development, and Python development with PyCharm. |
| Hands-on Exercises | This includes hands-on practical exercises that are usually intended to bridge any theoretical concepts or principles in software engineering. These activities kick off in the second week of the course and continue throughout the week. The exercises are usually completed in teams and students are encouraged to share knowledge and experience as an important part of the learning experience. These exercises include a mixture of project management and software development, such as: preparing a problem statement, writing a program, and scope of work, project deliverables, deliverables definition tables, project plan, demonstrating the familiarity with basic Java, Java Applications, building web applications from existing sources, deploying Java Web Applications, and demonstrating familiarity with Tomcat Development (Tomcat) and Unit Testing with JUnit, and demonstrated familiarity with Tomcat to deploy Java Applications. |
| Deliverables Demonstrations | Deliverables demonstrate the deliverables that are demonstrated or on real-class discussions. The deliverables demonstrate if individual or teams openly share their achievements, answer questions, and receive feedback from the rest of the class and the instructor. The discussions, thoughtfulness of evaluation of how the deliverables have been achieved and explanation of their delivered perspectives or possibilities, all done in a way that is focused on constructive problem-solving, highlighting connections to real-world situations, experience, and extends the collective thinking space. |
| Pre-Class & Post-Class | These are some pre-class and post-class resources that students were directed to use to drive additional investigations, to nurture problem-solving skills, and to challenge students to think out of the box. These include problem-solving videos, short tutorials on key topics, other relevant web resources, and programming practice examples or code from sources such as GitHub. |
| Assessment | The assessment of experiential learning activities involved both peer assessments, self-assessment, and instructor assessments of degree of demonstrated learning and/or problem-solving. The team-based assignments, the team project, exercises, and demonstrations required presentation, evidence, and communication elements. Students’ peer assessments recognized individual contributions to the accomplishment of the team’s objectives and level of personal investment in time and effort, creativity in generating ideas and evaluating them, collaboration, leadership, and leadership roles and responsibilities as assessment criteria. The assessment criteria were not only on the accomplishment of the team’s objectives but also demonstrated learning progress. |
| Unpacking | These are a series of open-ended activities designed to unpack the purpose of which was to offer opportunities for individual students or teams to examine the materials assigned by the instructor for the purpose of focused exploration of any aspect of the experiential learning activities and included assessment. This was an uneasiness to address any issues that may be confusing or ambiguous and needed decoding. It also reduced the thinking process that the students were not only on the accomplishment of the team’s objectives but also demonstrated learning progress. |
| Team Projects | The students work in teams and execute a software development project of their own choosing from scratch. The objective of the project is usually to tackle a specific or meaningful real-world problem for the team’s audience. The team project activity usually kicks off in the fourth week of the course, and teams progressively demonstrate weakly deliverables, and participate in weekly facilitated discussions on project progress, challenges encountered, new insights discovered, and get feedback throughout the course. |
### Table 13. Students’ perceptions indicators

| Index Code | Question Statement |
|------------|--------------------|
| 1. P10 | A course which incorporates practical hands-on activities to develop the experimental learning approach is more engaging |
| 2. P10 | A course which incorporates practical hands-on activities to develop the experimental learning approach is challenging |
| 3. P10 | A course which incorporates practical hands-on activities to develop the experimental learning approach is helpful in improving my knowledge |
| 4. P10 | A course which incorporates practical hands-on activities to develop the experimental learning approach is helpful in improving my understanding |
| 5. P10 | I would like to practice practical and hands-on activities in the course |
| 6. P10 | I was always able to take a course that incorporated hands-on activities to develop the experimental learning approach |
| 7. P10 | A course which incorporates practical hands-on activities to develop the experimental learning approach requires me to do a lot of independent work |
| 8. P10 | A course which incorporates practical hands-on activities to develop the experimental learning approach is more informative and I would gain relevant knowledge from it |
| 9. P10 | A course which incorporates practical hands-on activities to develop the experimental learning approach makes the learning process simpler |
| 10. | My knowledge and understanding of engineering principles and concepts improves when I am doing practical activities |
| 11. | I have a better understanding of the concepts through practical activities |
| 12. | A course which incorporates practical hands-on activities to develop the experimental learning approach is accessible to the engineering student |
| 13. | A course which incorporates practical hands-on activities to develop the experimental learning approach helps to familiarize students with industrial activities |
| 14. | A course which incorporates practical hands-on activities to develop the experimental learning approach helps me to develop myself |
| 15. | A course which incorporates practical hands-on activities to develop the experimental learning approach helps me to develop my knowledge |
| 16. | I am always interested in practical and hands-on activities |
| 17. | I am interested in practical and hands-on activities |
| 18. | I often used practical and hands-on activities and the course in general |
| 19. | My team is always interested in practical and hands-on activities to develop the experimental learning approach |
| 20. | My team is always interested in practical and hands-on activities to develop the experimental learning approach |
| 21. | My team is always interested in practical and hands-on activities to develop the experimental learning approach |
| 22. | I often use practical and hands-on activities and the course in general |
| 23. | I often use practical and hands-on activities and the course in general |
| 24. | I often use practical and hands-on activities and the course in general |
| 25. | I often use practical and hands-on activities and the course in general |
| 26. | I often use practical and hands-on activities and the course in general |
| 27. | I often use practical and hands-on activities and the course in general |
| 28. | I often use practical and hands-on activities and the course in general |
| 29. | I often use practical and hands-on activities and the course in general |
| 30. | I often use practical and hands-on activities and the course in general |
| 31. | I often use practical and hands-on activities and the course in general |
| 32. | I often use practical and hands-on activities and the course in general |
| 33. | I often use practical and hands-on activities and the course in general |
| 34. | I often use practical and hands-on activities and the course in general |
| 35. | I often use practical and hands-on activities and the course in general |
| 36. | I often use practical and hands-on activities and the course in general |
| 37. | I often use practical and hands-on activities and the course in general |
| 38. | I often use practical and hands-on activities and the course in general |
| 39. | I often use practical and hands-on activities and the course in general |
| 40. | I often use practical and hands-on activities and the course in general |
| 41. | I often use practical and hands-on activities and the course in general |
| 42. | I often use practical and hands-on activities and the course in general |
| 43. | I often use practical and hands-on activities and the course in general |
| 44. | I often use practical and hands-on activities and the course in general |
| 45. | I often use practical and hands-on activities and the course in general |

*Note. Each indicator was scored using a Likert scale (1=Strongly disagree, 2=Disagree, 3=Neutral, 4=Agree, 5=Strongly Agree). * Indicator was coded
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