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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,

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2013; SREB.org, 2016; Tuzun, Erdogmus, & Ozbilgin, 2018). Simultaneously, there is a growing demand for software engineers (Garousi et al., 2020; Tuzun et al., 2018).

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).

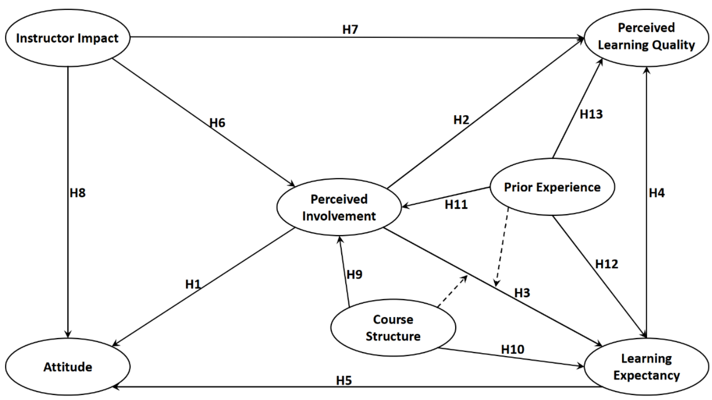
Variables that are relevant to involvement are also included in the study. The Unified Theory of Acceptance and Use of Technology (UTAUT) is often used to study attitude, intention, and behaviour in technology adoption (Alshare & Lane, 2011; Fauzi, Ali, & Amirudin, 2019; Sair & Danish, 2018). In addition, 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 & Albort-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.

Figure 1. The proposed study model (broken lines signify moderation).



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 (Lackéus & 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, Bõthe, 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 (Dvorak, 2017; Kock, 2019; Kock, Avison, & Malaurent, 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

Table 1. Factor loadings from CFA

Item	SA	SI	LE	QL	Communality
SP01	0.459				0.221
SP02	0.459				0.236
SP03	0.503				0.286
SP10	0.443				0.327
SP12	0.617				0.423
SP13	0.653				0.454
SP14	0.745				0.515
SP20	0.423				0.514
SP21	0.616				0.520
SP38	0.420				0.445
SP40	0.499				0.526
SP11		0.403			0.159
SP15		0.536			0.454
SP18		0.782			0.629
SP19		0.877			0.740
SP22		0.654			0.583
SP04			0.423		0.218
SP23			0.488		0.493
SP35			0.720		0.550
SP36			0.885		0.792
SP44			0.428		0.577
SP41				0.714	0.684
SP42				0.415	0.576
SP43				0.549	0.640
SP45				0.968	0.858

Index	Value	Intepretation
Root mean square of the residuals	0.070	acceptable if lower than 0.10
RMSEA index	0.064	below 0.05 (95%) for a good fit or 0.10 (90%)
Tucker-Lewis Index (TLI)	0.764	acceptable if greater than 0.90

Item	II	CS	Communality
SP25	0.670		0.486
SP26	0.565		0.301
SP27	0.647		0.714
SP28	0.545		0.467
SP29	0.490		0.452
SP30	0.834		0.575
SP31		0.685	0.621
SP32		0.601	0.390
SP33		0.860	0.692

Index	Value	Intepretation
Root mean square of the residuals	0.060	acceptable if lower than 0.10
RMSEA index	0.091	below 0.05 (95%) for a good fit or 0.10 (90%)
Tucker-Lewis Index (TLI)	0.901	acceptable if greater than 0.90

Note. *Loadings omitted if less than 0.40*

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,

Table 2. Latent variables and corresponding indicators

Latent Variable	Indicators	Description
Attitude (SA)	SP01, SP02, SP03, SP10, SP12, SP13, SP13, SP20, SP21, SP38, SP40	Students' attitudes toward the experiential learning course
CrsStruc	SP31, SP32, SP33	Students' perception of the impact of the course structure on their learning - representing whether objectives, expectations, outcomes, were clearly communicated and well-organized
InstrImp	SP25, SP26, SP27, SP28, SP29, SP30	Students' perceived level of instructor impact on the course - reflecting the degree to which the instructor was knowledgeable, the instructor's quality as a guide and mentor in the course
Exptancy (LE)	SP04, SP23, SP35, SP36, SP44	Students' learning expectancy or perception of the ease of use, perceived usefulness,in relation to the activities or course obligations
ExpLearn (SI)	SP11, SP15, SP18, SP19, SP22	Students' perception of the nature or quality of experiential learning activities on the course - representing the degree to which they students perceived their involvement or engagement
PriorExp	SP34	Student's perceived level of background knowledge and programming experience prior to the course
QuaLearn (QL)	SP41, SP42, SP43, SP45	Students' perceived quality of learning or experience

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 Sympson'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

Figure 2. Final estimated model, with instructor impact (InstrImp), student involvement (ExpLearn), attitude (Attitude), learning expectancy (Exptancy), quality of learning (QuaLearn), prior experience (PriorExp), and course structure (CrsStruc)

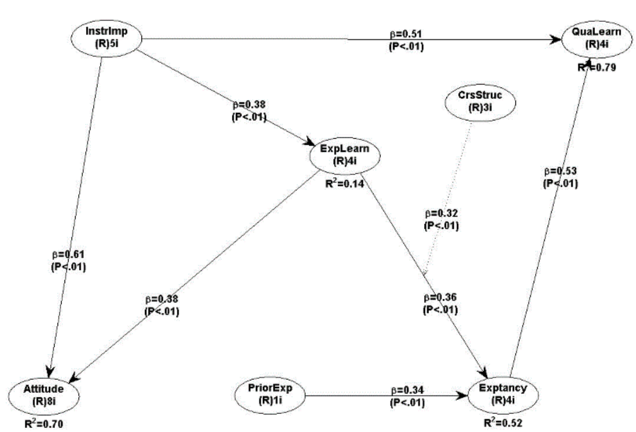


Table 3. Estimated model fit and quality indices

Index	Value	Interpretation
Average path coefficient (APC)	0.429	P<0.001
Average R-squared (ARS)	0.539	P<0.001
Average adjusted R-squared (AARS)	0.526	P<0.001
Average block VIF (AVIF)	1.234	acceptable if <= 5, ideally <= 3.3
Average full collinearity VIF (AFVIF)	2.750	acceptable if <= 5, ideally <= 3.3
Tenenhaus GoF (GoF)	0.553	small >= 0.1, medium >= 0.25, large >= 0.36
Sympson's paradox ratio (SPR)	1.000	acceptable if >= 0.7, ideally = 1
R-squared contribution ratio (RSCR)	1.000	acceptable if >= 0.9, ideally = 1
Statistical suppression ratio (SSR)	1.000	acceptable if >= 0.7
Nonlinear bivariate causality direction ratio (NLBCDR)	1.000	acceptable if >= 0.7

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 ρ	Cronbach's α	AVE	VIF	Weight	Loading	Effect Size
Attitude	0.866	0.861	0.660				
SP10				1.603	0.162†	0.566***	0.092
SP12				1.499	0.089	0.593***	0.053
SP13				1.980	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	0.067	0.745***	0.050
SP40				2.493	0.192*	0.761***	0.146
CrsStruc	0.790	0.787	0.744				
SP31				1.786	0.226*	0.758***	0.347
SP32				1.471	0.096	0.706***	0.114
SP33				1.844	0.406***	0.768***	0.203
InstrImp	0.823	0.814	0.687				
SP26				1.497	0.181*	0.590***	0.107
SP27				2.186	0.388***	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				
SP23				1.672	0.226*	0.704***	0.159
SP35				1.920	0.096	0.687***	0.066
SP36				2.504	0.406***	0.656***	0.266
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				1.876	0.388*	0.875***	0.340
PriorExp	1.000	1.000					
SP34				-	1.000***	1.000***	1.000
QuaLearn	0.870	0.869	0.789				
SP41				2.656	0.216*	0.802***	0.173
SP42				1.843	0.204*	0.780***	0.159
SP43				1.903	0.357***	0.827***	0.296
SP45				2.626	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	-0.062	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				2.556	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	0.503***	0.023
SP33^SP15				3.742	0.047	0.559***	0.026
SP33^SP18				5.220	0.083	0.688***	0.057
SP33^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	QuaLearn	Attitude	CrsStruc	PriorExp	CrsStruc^ExpLearn
InstrImp	(0.687)							
ExpLearn	0.359	(0.749)						
Exptancy	0.466	0.533	(0.718)					
QuaLearn	0.742	0.536	0.754	(0.789)				
Attitude	0.760	0.589	0.624	0.786	(0.660)			
CrsStruc	0.710	0.287	0.451	0.607	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	0.046	-0.178	(0.621)

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

Table 6. Vertical collinearity estimates

	InstrImp	ExpLearn	Exptancy	QuaLearn	Attitude	CrsStruc	PriorExp	CrsStruc^ExpLearn
Exptancy		1.319					1.030	1.351
QuaLearn	1.279		1.279					
Attitude	1.190	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 ρ	AVE	Full Collin. VIF	Q-squared
InstrImp			0.814	0.823	0.814	3.652	
ExpLearn	0.142	0.129	0.839	0.845	0.839	2.034	0.224
Exptancy	0.523	0.501	0.813	0.815	0.813	2.713	0.566
QuaLearn	0.786	0.780	0.869	0.870	0.869	5.025	0.791
Attitude	0.703	0.693	0.861	0.866	0.861	3.978	0.713
CrsStruc			0.787	0.790	0.787	2.143	
PriorExp			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	QuaLearn	Attitude
InstrImp					
ExpLearn		(1.041)			
Exptancy		-0.044	(1.070)		
QuaLearn		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).

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)		
Students' perceived involvement --> Students' learning expectancy (H3)	0.359***	0.196
Students' learning expectancy --> Perceived quality of learning (H4)	0.527***	0.402
Students' learning expectancy --> Students' attitudes (H5)		
Students' perceived level of instructor impact --> Students' perceived involvement (H6)	0.377***	0.142
Students' perceived level of instructor impact -->Perceived quality of learning (H7)	0.509***	0.384
Students' perceived level of instructor impact --> Students' attitudes (H8)	0.610***	0.465
Students' perceived impact of course structure --> Students' perceived involvement (H9)		
Students' perceived impact of course structure --> Perceived quality of expectancy (H10)		
Students' degree of prior experience --> Students' perceived involvement (H11)		
Students' degree of prior experience --> Students' learning expectancy (H12)	0.344***	0.147
Students' degree of prior experience --> Perceived quality of learning (H13)		
Students' perceived impact of course structure --> Students' learning expectancy (moderating)	0.324**	0.181

Note: †p<0.10, *p < 0.05, **p < 0.01, ***p < 0.001, one-tailed test.

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

	InstrImp	ExpLearn	Exptancy	PriorExp	CrsStruc^ExpLearn
InstrImp					
ExpLearn	0.377*** (1, 0.142)				
Exptancy	0.136* (1, 0.063)	0.359*** (1, 0.196)		0.344*** (1, 0.147)	0.324** (1, 0.181)
QuaLearn	0.580*** (2, 0.438)	0.189* (1, 0.101)	0.527*** (1, 0.402)	0.181* (1, 0.039)	0.170* (1, 0.013)
Attitude	0.754*** (2, 0.575)	0.380*** (1, 0.237)			

Note: †p<0.10, *p < 0.05, **p < 0.01, ***p < 0.001.

Table 11. Summary evaluation of hypotheses

Hypothesis	Supported
Students' perceived involvement --> Students' attitudes (H1)	Yes
Students' perceived involvement --> Perceived quality of learning (H2)	No
Students' perceived involvement --> Students' learning expectancy (H3)	Yes
Students' learning expectancy --> Perceived quality of learning (H4)	Yes
Students' learning expectancy --> Students' attitudes (H5)	No
Students' perceived level of instructor impact --> Students' perceived involvement (H6)	Yes
Students' perceived level of instructor impact -->Perceived quality of learning (H7)	Yes
Students' perceived level of instructor impact --> Students' attitudes (H8)	Yes
Students' perceived impact of course structure --> Students' perceived involvement (H9)	No
Students' perceived impact of course structure --> Perceived quality of expectancy (H10)	No
Students' degree of prior experience --> Students' perceived involvement (H11)	No
Students' degree of prior experience --> Students' learning expectancy (H12)	Yes
Students' degree of prior experience --> Perceived quality of learning (H13)	No
Students' perceived impact of course structure --> Students' learning expectancy (moderating)	Yes

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 (β=0.580, P<0.001), student involvement (β=0.377, P<0.001), and attitudes (β=0.754, P<0.001). Student involvement positively correlated with attitude (β=0.380, P<0.001), learning expectancy (β=0.359, P<0.001), but only indirectly with quality of learning (β=0.189, P<0.011) through learning expectancy. Similarly, learning expectancy positively correlated with quality of learning (β=0.527, P<0.001) but not attitude. Instructor impact positively correlated with student involvement (β=0.377, P<0.001), quality of learning (β=0.509, P<0.001), and attitude (β=0.610, P<0.001). Instructor impact also positively correlated indirectly with attitudes (β=0.144, P<0.043), learning expectancy (β=0.136, P<0.053), but not quality of learning (β=0.071, P<0.152). Therefore, any indirect effect on the quality of learning was solely because of student involvement. Prior experience positively correlated 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 (R^2=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
Expectations Discussion	A critical component of participation. The first assignment in the first week of the course in which students openly discuss their expectations relating to the course with peers and the instructor. The discussions usually broadly include student's interest in the course, reasons for taking the course, prior exposure to or experience with experiential learning, what each student brings to the course in terms of prior knowledge and/or software development or programming experience, what each student expected to gain or learn from the course, and how each student expected the course to be beneficial to them. The instructor also participates in the discussions by answering any questions, particularly about experiential learning - particularly explaining the assessment methodology and tool, in an open and candid way as well as sharing their own experiences on real-world projects in the software industry.
Tools & Environment Setups	This includes all the preparatory activities aimed at leveling the playing field to ensures that all students acquire the readiness needed to work independently and to contribute to team work 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 coaching and guidance is critical in providing meaningful real-world justification for the acativities and ensuring all students actively participate in the activities and can follow the documented notes and activity steps. The preparatory tools and setups to support hands-on exercises include: preparing and setting up each student's laptop for software development (i.e., configuring environment variables); installing and configuring Java SDK, MySQL Community Edition, and MySQL Workbench, Apache Tomcat, NetBeans IDE; installing and activating all necessary NetBeans Plugins including the appropriate Struts plugins; and installing SceneBuilder for Rich Client application development; installing and introducing tools needed for test-driven development such as JUnit.
Hands-on Exercises	These are regular weekly hands-on practical exercises that are usually intended to bring to life any theoretical concepts or principles in software engineering. These activities kick-off in the second week of the course and continue throughout on a weekly basis. The exercises are usually completed in teams and students are encouraged to share knowledge and experiences as an important part of the learning experience. The exercises include a mixture of project management and software development - such as, preparing a team charter, statement of work, and scope of work, project deliverables, deliverables definition tables, project plans; demonstrated familiarity with basic Java, Java Applications, building Java Web Applications from existing sources, deploying Java Web Applications, demonstrated familiarity with Test-Driven Development (TDD) and Unit Testing with JUnit, and demonstrated familiarity with TDD to refactor Java Applications.
Deliverable Demonstrations	All hands-on activities and team project deliverables have either a demonstration or in-class discussion component. The demonstrations offer opportunities for individuals or teams to openly share their achievements, answer questions, and receive feedback from the rest of the class and the instructor. The discussions thoughtful evaluations of what has been achieved and exploration of other offered perspectives or possibilities - all done in a way that is focused on constructive problem-solving, highlighting connections to real-world situations or experiences, and expands the collective thinking space
Pre-Class & Post-Class	There were 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 from outside the box. These included problem-solving videos, short quizzes to test knowledge on topics, other relevant web resources, and programming practice examples or code from sources such as GitHub.
Assessment	The assessment of the experiential learning activities involved both peer-assessments on activities accomplished and instructor assessments of degree of demonstrated learning and/or problem-solving. The team-based assignments, the team project, exercises, and demonstrations required preparation, execution, and communication elements. Students' peer assesments recognized individual contributions to the accomplishment of the tasks - in terms of level of personal investment in time and effort, creativity in generating ideas and evaluating them, collaboration, leadership, or going above and beyond and these assessments were weighted together with the instructor's assessment to produce overall scores.
Unpacking	There were periodic or on-demand ungraded unpacking sessions the purpose of which was to offer an opportunity for individual students or teams to meet with the instructor for the purpose of focused exploration of any aspects of the experiential learning activities including assessment. This was an avenue to address any issues that may be confusing or ambiguous or needed decoding, and also refocusing on the big picture - the key essence being that the assessments were not only on the accomplishment of the tasks but also demonstrated learning progression
Team Projects	The students work in teams to plan and execute a software development project of their own chosing from scratch, the objective of the project is usually to tackle a specific or meaningful real-world problem for a target audience. The team project activities usually kick-off in the fourth week of the course, and teams progressively demonstrate weekly project 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 SP01	A course which incorporates practical hands-on activities or adopts the experiential learning approach is interesting
2 SP02	A course which incorporates practical hands-on activities or adopts the experiential learning approach is satisfying
3 SP03	A course which incorporates practical hands-on activities or adopts the experiential learning approach encourages active engagement and involvement
4 SP04*	A course which incorporates practical hands-on activities or adopts the experiential learning approach is challenging
5 SP05	I would like more practical hands-on activities incorporated in courses
6 SP06	I would be glad to take a course that incorporates hands-on activities or adopts the experiential learning approach
7 SP07	A course which incorporates practical hands-on activities or adopts the experiential learning approach requires me to exercise independent judgment in evaluating theoretical concepts
8 SP08	A course which incorporates practical hands-on activities or adopts the experiential learning approach is more informative and I would gain relevant knowledge from it
9 SP09	A course which incorporates practical hands-on activities or adopts the experiential learning approach makes the learning process simpler
10 SP10	My knowledge and problem-solving confidence will grow if I take a course which incorporates practical hands-on activities or adopts the experiential learning approach
11 SP11*	Incorporating practical hands-on or experiential activities increases the workload involved in learning and integrating the course materials
12 SP12	A course which incorporates practical hands-on activities or adopts the experiential learning approach is applicable to the real-world and building my career
13 SP13	A course which incorporates practical hands-on activities or adopts the experiential learning approach helps to develop professional skills
14 SP14	A course which incorporates practical hands-on activities or adopts the experiential learning approach helps me to develop myself
15 SP15	I very actively interacted with others or engaged in the planned activities and/or used the recommended tools
16 SP16	I readily recognized or willingly took steps to solve problems if/when they arose during the hands-on activities and the course in general
17 SP17	I often used prior knowledge to make decisions during the hands-on exercises and the course in general
18 SP18	My team's reflections on the experiences with the hands-on activities helped me to process the lessons and to improve my understanding of the concepts and my approach problems
19 SP19	My team's reflections helped me to recognizing and describe my personal biases and see other perspectives to challenges
20 SP20	The hands-on activities helped me apply and adapt knowledge and/or skills learned during the exercises, or to make connections between the practical activities and academic theory or concepts during the course
21 SP21	The hands-on activities helped me to be aware and understand the complexity of issues and situations involved in solving problems
22 SP22	Working with my team on the hands-on project or exercises prepared me to be able to identify and analyze the implications of issues that occur, decisions, actions, and on me and others
23 SP23	The hands-on exercises provided opportunities for me to come up with creative solutions to some problems or challenges
24 SP24	As a result of the hands-on practical exercises, I have been able to reflect on what I learned and I am better prepared to integrate the lessons learned into any future software projects
25 SP25	The Instructor was very knowledgeable about course and field
26 SP26	The Instructor presented materials or led discussions in an organized fashion and emphasized important points
27 SP27	The Instructor communicated effectively, explained well, presented content clearly, and gave understandable responses to questions
28 SP28	The Instructor was dynamic and energetic, stimulated learner interest, and enjoyed teaching
29 SP29	The Instructor demonstrated role model qualities that were of use or motivating or engaging to students
30 SP30	The Instructor was concerned about students learning the material, encouraged the to participate, was receptive to different or other perspectives
31 SP31	The course objectives and procedures of the course were clearly communicated - e.g., via the syllabus and on the Canvas LMS
32 SP32	The course materials were organized into logical and understandable components - e.g., via the syllabus and on the Canvas LMS
33 SP33	The course expectations were clearly stated - e.g., via the syllabus and via the Canvas LMS
34 SP34	I had some prior background software programming or development experience coming into the course
35 SP35	I found that learning to do or participating in or engaging in the experiential learning or hands-on activities was easy for me
36 SP36	I found actually doing or participating in or engaging in the experiential activities or hands-on activities was easy for me
37 SP37	I found the instructions and guidance notes for the experiential activities or hands-on exercises clear and understandable
38 SP38	I believed or was confident that doing the experiential or hands-on activities would be useful in my degree program
39 SP39	I believed or was confident that doing the experiential or hands-on activities would improve me knowledge and skills
40 SP40	I believed or was confident that doing the experiential or hands-on activities would be useful in my subsequent career
41 SP41	I was satisfied overall with the course
42 SP42	I would recommend the course to other students
43 SP43	I learned the required or important information and skills
44 SP44	I gained confidence in my ability to solve related problems
45 SP45	I was satisfied with the overall quality of the learning experience

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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