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Developing a Learning Analytics-Based Framework for ESP in Construction Management

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ABSTRACT

In the era of digital construction, effective communication, particularly in English has become essential for professionals in construction project management. However, many English for Specific Purposes (ESP) programs still rely on generic instructional approaches that fail to address the real communication challenges and digital literacy needs of future construction managers. Moreover, the potential of learning analytics to enhance language instruction in technical fields remains underutilized. This study develops a learning analytics-based framework for ESP instruction tailored to the digital construction management context. The research is guided by three objectives: (1) to identify the specific English language limitations in digital communication challenges faced by construction management students, (2) to explore how learning analytics can help overcome the identified language needs and communication challenges through personalized ESP instruction, and (3) to develop a learning analytics-based ESP framework that addresses the identified language needs and communication challenges by incorporating critical success factors for effective, data-driven instruction in construction education. A quantitative research design was employed, using structured questionnaires to collect data from undergraduate and postgraduate civil engineering students specializing in construction project management. The data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). The findings informed the development of a practical, evidence-based framework that enhances language instruction through adaptive learning strategies and digital performance tracking. This research contributes to both construction education and applied linguistics by bridging the gap between domain-specific language training and data-informed educational technologies.

Keywords: English for specific purposes (ESP), construction project management, learning analytics, digital communication, PLS-SEM, quantitative analysis

INTRODUCTION

In the era of digital construction, English communication has become a critical competency for professionals in construction project management. As international collaboration, digital tools, and BIM-based workflows become more widespread, professionals must be able to engage in effective technical communication across platforms and cultures (Ismail et al., 2021; Omar & Ali, 2023). English for Specific Purposes (ESP) offers a focused approach to developing discipline-specific communication skills; however, ESP instruction in construction education often lacks contextual alignment with actual digital project environments (Rahman et al., 2022; Hutchinson & Waters, 1987).

Despite the growth of digital learning, most ESP programs do not utilize learning analytics to personalize instruction or assess learners' needs in real time (Fadzil et al., 2023; Yin et al., 2020). Consistent with these observations, Othman et al. (2024) emphasized how digital innovations such as ChatGPT are being integrated into language pedagogy to support personalized and interactive learning, reinforcing the importance of aligning ESP instruction with technology-enhanced practices.

This study addresses that gap by identifying the specific English language needs and communication challenges faced by construction students in digital contexts and examining how learning analytics can support performance-based, adaptive ESP instruction. A quantitative method will be used, collecting data via structured questionnaires. The data will be analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) to develop a learning analytics-based ESP framework tailored to the needs of construction project management education.

English for Specific Purposes (ESP) in Technical and Professional Contexts

ESP is an instructional approach designed to meet the specific language needs of learners in particular disciplines or professions. In technical fields such as construction and engineering, ESP focuses on tasks like report writing, documentation, stakeholder communication, and technical reading (Hutchinson & Waters, 1987; Basturkmen, 2010). However, ESP courses in many institutions still rely on general English content, disconnected from the context of construction practice. According to Rahman et al. (2022), such generalist approaches fail to equip learners with the skills to engage in field-specific communication, particularly in increasingly digital environments. Thus, there is a need to realign ESP instruction with the actual linguistic demands of the construction industry, including documentation, specifications, and technical briefings.

Communication Needs and Challenges in Construction Project Management

The construction industry today is shaped by globalized workflows and cross-border collaboration. Construction professionals must regularly engage in English-based communication with international stakeholders via project emails, BIM platforms, digital dashboards, and site reports (Ismail et al., 2021; Omar & Ali, 2023). However, many students entering the field struggle with these modes of communication due to limited exposure during their academic training (Mohd Noor & Tan, 2021). Challenges include understanding specialized terminology, managing tone in professional writing, and interpreting multi-format information from digital platforms. These issues represent a clear mismatch between language instruction and workplace expectations, justifying the first objective: to identify the actual English language needs and communication difficulties faced by construction students.

Learning Analytics in Language Education

Learning analytics involves collecting, analyzing, and using data about learners and their activities to improve teaching and learning outcomes (Siemens & Long, 2011). In language education, learning analytics has been applied to track vocabulary acquisition, monitor student participation in online activities, and personalize content delivery (Yin et al., 2020). Studies have found that learning analytics can support learner autonomy, provide immediate feedback, and improve engagement by adapting to students' performance in real time. However, its application in ESP especially for construction and engineering students, is still at a preliminary stage. Most ESP programs continue to rely on static instruction models with limited responsiveness to learner progress or difficulties (Fadzil et al., 2023). This gap highlights the need to explore how learning analytics can enhance ESP delivery, fulfilling the second research objective.

The Role of Learning Analytics in Construction and Engineering Education

While learning analytics has shown positive results in general education, its integration into construction and engineering programs has become increasingly relevant. Analytics dashboards are used to monitor student progress in BIM training, track engagement in project-based learning, and identify patterns that predict academic success (Yusof et al., 2022). Tools such as digital progress tracking and automated performance feedback can help students develop critical professional competencies, including communication. Abubakar et al. (2021) argue that analytics from BIM interactions, document submissions, and collaborative tasks can be used to assess communication efficiency and information exchange in construction teams. However, few studies have applied this potential specifically to language instruction, further justifying the need for targeted research into how learning analytics can support ESP for construction students.

Frameworks in ESP and Learning Analytics Integration

Existing ESP frameworks in engineering education tend to focus on content selection, skill-based progression, and learner needs analysis (Basturkmen, 2010). While some integrate instructional technologies, few incorporate learning analytics as a formal component. Recent research has highlighted the value of integrating analytics tools into language instruction to enable data-driven decision-making and continuous improvement (Fadzil et al., 2023). Likewise, Raslee (2020) demonstrated how digital storytelling tasks impact language accuracy, supporting the idea that ESP frameworks should incorporate creative, data-informed digital activities. Nonetheless, there is a lack of frameworks that combine ESP with analytics systems in a way that is customized for digital construction environments. The theoretical foundations for such a model lie in constructivist learning theory which emphasizes contextualized, learner-centered instruction, and data-informed instruction, which relies on empirical performance data to guide teaching strategies. These frameworks support the third research objective: to design a learning analytics-based ESP framework tailored to the needs of construction project management students.

METHODOLOGY

As the foundation of the research strategy, both qualitative and quantitative approaches were used to accomplish the study's goals. As described below, the study was methodically carried out in three primary stages.

Phase 1: Literature Review, Problem Analysis, and Questionnaire Design

The first phase of the study involves an extensive literature review, problem identification, and the design of a structured questionnaire. The literature review focuses on three key areas: (i) English for Specific Purposes (ESP) in technical education, particularly within the construction domain, (ii) communication challenges in digital construction management, and (iii) the application of learning analytics in language education. This review establishes a theoretical foundation for identifying existing research gaps and informing the development of the conceptual framework (Basturkmen, 2010; Hutchinson & Waters, 1987; Siemens & Long, 2011). Simultaneously, a problem analysis is conducted by synthesizing academic findings with contextual insights from recent industry reports and institutional curricula to pinpoint the misalignment between current ESP instruction and digital communication needs in construction management (Rahman et al., 2022; Ismail et al., 2021).

Based on the insights gained, a structured questionnaire is designed to capture the perceptions, needs, and challenges of construction management students related to English language usage and digital communication. The questionnaire comprises four major sections: demographic background, English language needs, digital communication challenges, and perceived usefulness of learning analytics in ESP instruction. Items are primarily measured using a five-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree), following validated scales adapted from previous studies (Yin et al., 2020; Fadzil et al., 2023). The instrument is reviewed by domain experts in ESP and construction education to ensure face and content validity. A pilot test is conducted with 15 students to assess reliability using Cronbach's Alpha and to refine the instrument before full-scale deployment.

Phase 2: Data Collection and Analysis

The administration of the validated questionnaire and the ensuing data analysis comprise the second phase. Undergraduate and graduate students participating in construction management programs at a few Malaysian universities make up the target population. The Partial Least Squares Structural Equation Modeling (PLS-SEM) guidelines, which call for a minimum of 200 participants or ten responses per indicator in the most complicated construct to guarantee model validity, are used to estimate the minimum sample size. A total of 65 students were chosen to participate in this survey as respondents. Given that the study's maximum number of indicators is six (6), which necessitates a minimum of 60 respondents according to the recommendation of 10 responses per indicator, this sample size is enough (Hair et al., 2021).

The collected data is exported and analyzed using PLS-SEM, a robust statistical technique suitable for exploratory studies involving latent constructs and non-normally distributed data (Hair et al., 2021). Assessment of the measurement model and evaluation of the structural model are the two phases of the analysis. As seen in Table 1, the first step evaluates the constructs' validity and reliability using Composite Reliability (CR), Cronbach's Alpha, Average Variance Extracted (AVE), and Discriminant Validity using the Fornell-Larcker criterion. As shown in Table 2, the second step involves evaluating the structural model to investigate the proposed links between constructs using path coefficients, coefficient of determination (R2), effect size (f2), and path coefficient (β). The efficiency of ESP and the mediating function of learning analytics can be identified thanks to this analytical technique.

Table 1. Assessment aspects and criterion for measurement model

Assessment Aspect	Criterion (s)	Accepted Values or Conditions
Indicator Reliability	Indicator Loadings	Items with 0.70 or above are regarded as highly satisfactory. In exploratory study designs, measurement variables (MVs) with loadings of 0.40 or higher are considered acceptable, while those below 0.40 should be removed from the analysis.
Internal Consistency Reliability	Cronbach's Alpha (CA) Composite Reliability (CR)	Confirmative study: 0.70 > CA/CR > 0.90 Explorative study: 0.60 > CA/CR > 0.70
Convergent Validity	Average Variance Extracted (AVE)	Proposed threshold value: AVE > 0.50
Discriminant Validity	Cross-loadings Fornell-Larcker criterion	Indicators should load more strongly on their own construct than on other constructs. The Average Variance Extracted (AVE) of each construct must be higher than its squared correlation with any other construct (shown in bold on the diagonal).

Table 2. Assessment aspects and criterion for structural model

Assessment Aspect	Criterion (s)	Accepted Values or Conditions
Explanatory Power	Coefficient of determination (R^2) Effect size (f^2)	When the R^2 value is 0.26 = good, 0.13 = moderate, and 0.02 = weak. 0.02 - 0.15 = small, 0.15 - 0.35 = medium, > 0.35 = large
Predictive Power	Path Coefficient (β)	Path coefficients must be at least 0.10 to account for a certain impact within the model.

Phase 3: Framework Development

The final phase synthesizes the empirical findings into the development of a Learning Analytics-Based ESP Framework specifically tailored for construction management education. Drawing on the validated relationships identified through PLS-SEM analysis, the framework integrates the key components influencing ESP instruction: learner-specific English language needs, digital communication challenges, and the strategic use of learning analytics tools. The framework is structured to align with principles of constructivist learning theory, emphasizing learner-centered instruction, contextual relevance, and adaptive feedback (Jonassen, 1991; Siemens & Long, 2011). It incorporates feedback loops using learning analytics to inform instructional adjustments, real-time performance tracking, and personalized language learning pathways.

To ensure practical relevance, the framework is subjected to expert validation involving academic professionals in ESP, digital education, and construction management. Their feedback is used to refine the framework for eventual implementation in higher education institutions. This phase concludes with the articulation of implementation guidelines and recommendations for curriculum integration, offering a scalable model for enhancing ESP instruction through data-driven decision-making in digital construction education contexts.

RESULTS AND ANALYSIS

Pilot Study - Data Reliability

A total of 15 respondents took part in the pilot study, comprising (5) from students in semester 5 and 10 students in Semester 6. The reliability analysis, evaluated through Cronbach's alpha values, demonstrated high reliability of the variables, with acceptable values above 0.5 and preferable values exceeding 0.7 (Hair et al., 2010). As shown in Table 3, the English Language Limitations (ELL) comprising 6 items achieved a Cronbach's alpha of 0.805. Similarly, the Digital Communication Difficulties (DCD) category with 5 items recorded an alpha value of 0.811, while the Learning Analytics in Personalized ESP Instruction (LA) with 5 items reported an alpha value of 0.798 and finally for Critical Success Factors (CSFs) with 6 items recorded alpha value of 0.912.

Table 3. Value of Cronbach's Alpha

Item to be Analysis	Values of Alpha
English Language Limitations (ELL) ELL1-Limited Technical Vocabulary Proficiency ELL2-Weak Report Writing Skills ELL3-Inadequate Grammar and Sentence Structure ELL4-Lack of Familiarity with Instructional Language ELL5-Low Confidence in Public Speaking ELL6-Difficulty in Writing for Professional Purposes	0.805
Digital Communication Difficulties (DCD) DCD1-Difficulty Writing Professional Emails DCD2-Challenges Using English in BIM or Project Software DCD3-Inability to Interpret Technical Digital Reports DCD4-Struggles with Multi-Modal Content DCD5-Confusion with Digital Construction Terminology	0.811
Learning Analytics in Personalized ESP Instruction (LA) LA1-Use of Learning Analytics for Real-Time Performance LA2-Feedback and Error Detection Through Analytics LA3-Personalized Content Recommendation LA4-Student Engagement Monitoring LA5-Predictive Analytics for Language Learning Outcomes	0.798
Critical Success Factor (CFs) CFS1-Integration of Learning Analytics Tools CFS2-Communication Challenges CFS3-Personalized Learning Pathways CFS4-Real-Time Feedback and Diagnostic Reporting CFS5-Instructor Decision Support System CFS6-Learner Autonomy Features	0.912

Measurement Model Analysis

The PLS-SEM analysis, encompassing both measurement and structural model evaluations, was subsequently conducted. The assessment of the measurement model confirmed that all reliability and validity requirements were met in this study.

Indicator Reliability

According to Hair et al. (2010), in exploratory studies, factor loadings of 0.40 are considered acceptable, while items with loadings below 0.40 should be removed. In the measurement model analysis (Table 4), two items in English Language Limitations (ELL3 and ELL4) and one item in

Digital Communication Difficulties (DCD1) were removed due to indicator loading values below the 0.40 threshold, as recommended by Hair et al. (2010). Both Cronbach's Alpha (CA) and Composite Reliability (CR) values exceeded 0.70, and the Average Variance Extracted (AVE) values were above 0.50, confirming the model's validity.

Table 4. Summary of the Measurement Model Analysis Using PLS-SEM 4.0

Variable Groups	PLS Algorithm				
	Symbol	Loading	AVE	CR	CA
English Language Limitations:					
Limited Technical Vocabulary	ELL1	0.809	0.641	0.815	0.812
Proficiency	ELL2	0.822			
Weak Report Writing Skills	ELL5	0.841			
Low Confidence in Public Speaking	ELL6	0.725			
Difficulty in Writing for Professional Purposes					
Digital Communication Difficulties:					
Challenges Using English in BIM or Project Software	DCD2	0.870	0.743	0.887	0.885
Inability to Interpret Technical Digital Reports	DCD3	0.844			
Struggles with Multi-Modal Content	DCD4	0.879			
Confusion with Digital Construction Terminology	DCD5	0.854			
Learning Analytics in Personalized ESP Instruction:					
Use of Learning Analytics for Real-Time Performance	LA1	0.888	0.813	0.944	0.942
Feedback and Error Detection Through Analytics	LA2	0.865			
Personalized Content Recommendation	LA3	0.929			
Student Engagement Monitoring					
Predictive Analytics for Language	LA4	0.892			
Learning Outcomes	LA5	0.931			
Critical Success Factor:					
Integration of Learning Analytics Tools	CFS1	0.880	0.682	0.914	0.906
Communication Challenges	CFS2	0.788			
Personalized Learning Pathways	CFS3	0.840			
Real-Time Feedback and Diagnostic Reporting	CFS4	0.874			
Instructor Decision Support System	CFS5	0.727			
Learner Autonomy Features	CFS6	0.835			

Internal Consistency Reliability

Cronbach's Alpha (CA) and Composite Reliability (CR) are two key indicators used to assess internal consistency reliability. These measures indicate how effectively a set of items evaluates a specific construct. According to Henseler et al. (2015), the recommended threshold for internal consistency reliability should be no less than 0.60, with values above 0.70 being more desirable. As presented in Table 4, both CA and CR values in the initial and final iterations of the PLS-Algorithm exceed 0.70, demonstrating that each set of the factors reliably measures its respective construct.

Convergent Validity

Convergent validity refers to the extent to which a construct captures variance from its related indicators, accounting for measurement errors (Henseler et al., 2009). This validity is assessed using the Average Variance Extracted (AVE), where at least 50% of the variance should be explained by the construct it represents (Hair et al., 2010). As shown in Table 7, the runs of the PLS algorithm produced AVE values exceeding 0.50.

Discriminant Validity

Discriminant validity is a form of construct validity used in PLS-SEM to determine the extent to which a construct is distinct and uncorrelated with other dissimilar constructs (Hulland, 1999). According to the Fornell-Larcker criterion, the Average Variance Extracted (AVE) for each construct should be higher than the squared correlations with any other construct (Fornell & Larcker, 1981). As shown in Table 5, the off-diagonal AVE values are smaller than the diagonal AVE values (highlighted in bold), confirming the discriminant validity of the model.

Table 5. Discriminant Validity Analysis

	CFs	DCD	ELL	LA
CFs	**0.826**			
DCD	0.795	**0.862**		
ELL	0.718	0.762	**0.800**	
LA	0.897	0.852	0.719	**0.901**

Cross-loadings are used for the subsequent evaluation of discriminant validity. As shown in Table 6, cross-loadings for all the factors have greater values on their relative group when compared to the other group, either in the same row or column. This demonstrates that the components in each construct accurately reflect the designated group, supporting the measurement model's discriminant validity as shown in Figure 1.

Table 6. Cross-Loading Analysis

	CFs	DCD	ELL	LA
CFS1	**0.880**	0.737	0.618	0.832
CFS2	**0.788**	0.611	0.630	0.706
CFS3	**0.840**	0.670	0.561	0.756
CFS4	**0.874**	0.719	0.617	0.826
CFS5	**0.727**	0.591	0.574	0.599
CFS6	**0.835**	0.594	0.565	0.693
DCD2	0.693	**0.870**	0.650	0.727
DCD3	0.687	**0.844**	0.673	0.689
DCD4	0.715	**0.879**	0.634	0.714
DCD5	0.650	**0.854**	0.670	0.797
ELL1	0.541	0.611	**0.809**	0.533
ELL2	0.581	0.678	**0.822**	0.623
ELL5	0.577	0.674	**0.841**	0.580
ELL6	0.597	0.466	**0.725**	0.558
LA1	0.765	0.826	0.643	**0.888**
LA2	0.688	0.766	0.585	**0.865**
LA3	0.871	0.770	0.660	**0.929**
LA4	0.846	0.728	0.635	**0.892**
LA5	0.863	0.751	0.712	**0.931**

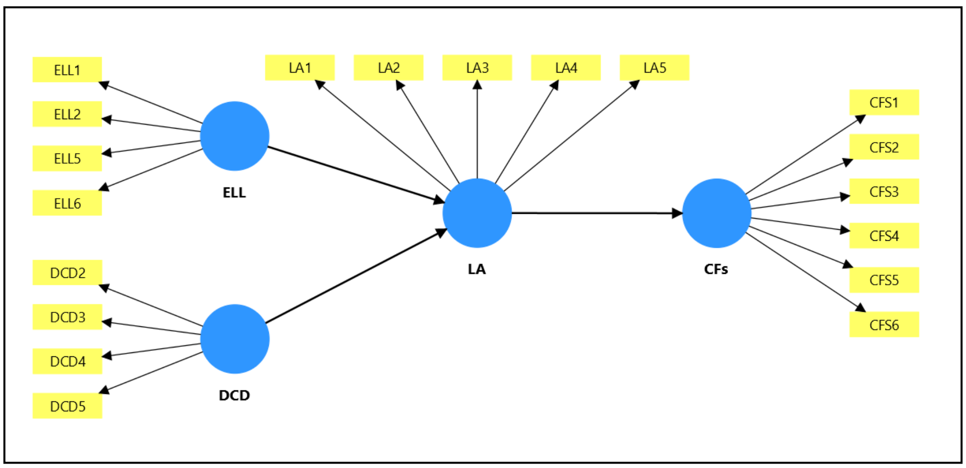

Figure 1. Measurement Model

Structural Model Assessment

The assessment of the structural model is the second phase of evaluation. This occurs after the validity and reliability of the measurement model have been established. The structural model employs a path diagram to investigate the relationships among ELL, DCD, LA, and CFs. Two components are involved in the evaluation of the structural model:

1) Explanatory Power: The criteria are the Effect Size (f^2) and the Coefficient of Determination (R^2)
2) Path Coefficient (β) for predictive power

Explanatory Power

The Coefficient of Determination (R^2) is used in this analysis to measure the explained variance for each group's components. According to Cohen (1997), the R^2 value for an endogenous construct can be interpreted as 0.26 = substantial, 0.13 = moderate, and 0.02 = weak. As shown in Table 7 and Figure 2, the construct linking the ELL and DCD to LA explains 73.7% of the variance. Meanwhile, the constructs connecting LA to CFs account for 80.5% of the variance. Overall, the model demonstrates a substancial performance, as all R^2 values exceed the recommended threshold.

Table 7. Results of Coefficient of Determination (R^2)

Relationship	Coefficient of Determination (R^2)	Result
ELL > LA	0.737	Good (Substantial)
DCD > LA	0.737	Good (Substantial)
LA > CFs	0.805	Good (Substantial)

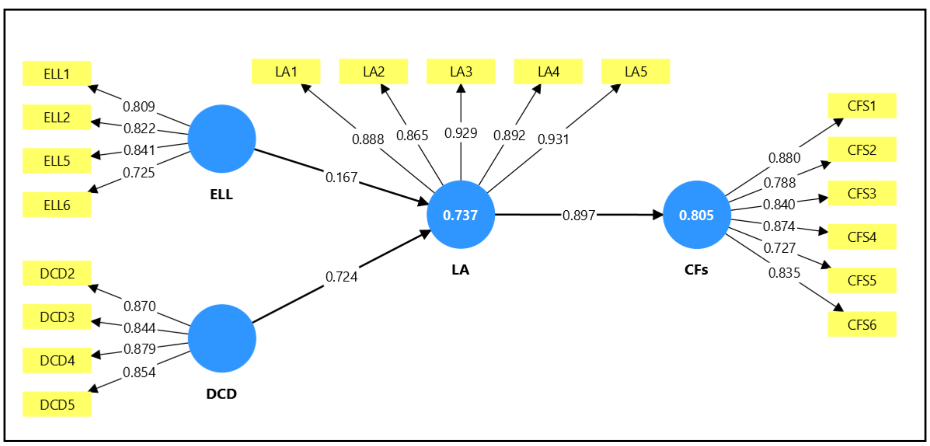

Figure 2. Coefficient of determination (R^2)

The effect size value (f^2) in Table 8 illustrates the strength of the relationship between each group to the CFs. According to Cohen (1997), an effect size below 0.02 is considered small, while values above 0.35 are classified as large. For this study, one relationship (ELL > LA) is considered small and another two (2) relationships between variables are larger than 0.35, resulting moderate effect size, according by Cohen (1997); hence the model lies at a Substantial level.

Table 8. Results of effect size value (f^2)

Relationship	Coefficient of Determination (R^2)	Result
ELL > LA	0.045	Small
DCD > LA	0.835	Large
LA > CFs	4.135	Large

Predictive Power

Table 9 shows that for two relationships, DCD: LA and LA: CFs, the values obtained are higher than the cut-off point value of 0.10. Relation of LA:CFs has the highest value for the variable category that has the strongest correlation with CFs (β = 0.897), followed by DCD: LA (β = 0.724). The t-values are more than the cut-off significance value, which is 0.05 or 5% at the very least. This indicates that just two variable groups which are LA:CFs (t=21.769) and DCD:LA (t=5.101) have a significant relationship. Figure 3 shows the overall result of the path coefficient in the PLS-SEM Structural Model.

Table 9. Results of Hypothesis Tests

Hypothesis	Relationship	Path Coefficient, β	t-Value	p -values	Remarks
H1	DCD -> LA	0.724	5.101	0.000	**Significant*** **
H2	ELL -> LA	0.167	1.107	0.268	**Not Significant**
H3	LA -> CFs	0.897	21.769	0.000	**Significant*** **

Note: Significance value: *p<0.1 (t>1.64), **p<0.05 (t>1.96), ***p<0.01 (t>2.58)

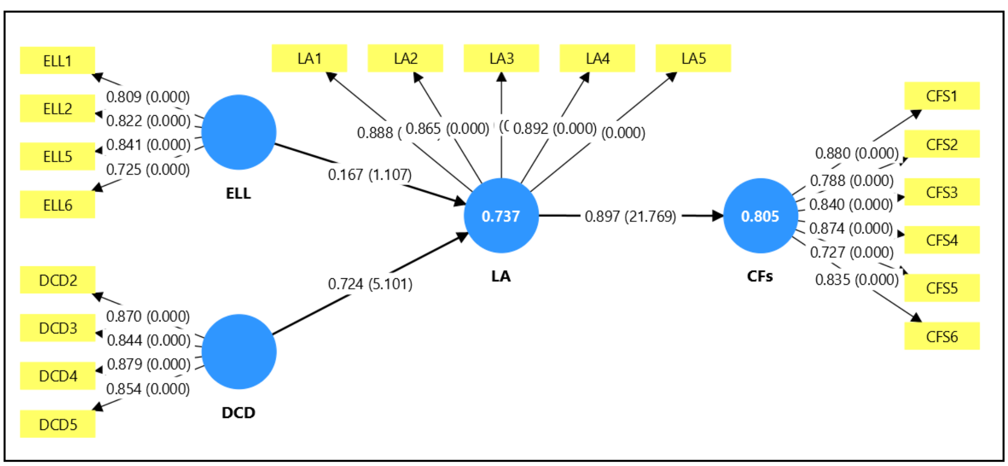

Figure 3. Structural Model

CONCLUSION

The data indicates that the first three objectives were successfully met using various analytical methods. The analysis was conducted using PLS-SEM 4.0, which included two phases: first, assessing the measurement model, and second, evaluating the structural model. In the measurement model assessment, processes for reliability and validity resulted in the removal of several items from the constructs. In the second phase, the structural model was examined to determine its explanatory and predictive capabilities. The results supported the hypothesis that significant relationships exist between the two groups of variables; "**Digital Communication Difficulties (DCD): Learning Analytics in Personalized ESP Instruction (LA)"** and **"Learning Analytics in Personalized ESP Instruction (LA): Critical Success Factor (CFs)"** which contribute to a Learning Analytics-Based Framework for ESP in Construction Management.

Future research should focus on implementing and evaluating the proposed learning analytics-based ESP framework in real classroom or online environments to assess its effectiveness in improving students' language and communication performance. Comparative studies across institutions or countries are also encouraged to explore its adaptability. Additionally, research should examine instructors' use of learning analytics dashboards and their impact on teaching practices. Further investigation into integrating the framework with industry platforms like BIM, as well as incorporating gamification, mobile learning, and AI-driven predictive analytics, could enhance personalization and learner engagement. Finally, ethical considerations regarding learner data privacy in ESP contexts should also be explored.

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Declaration of Generative AI and AI-assisted Technologies in the Writing Process

During the preparation of this work, the authors used **ChatGPT (OpenAI, GPT-5)** to support language refinement, grammar checking, and to improve clarity and conciseness of expression. The tool was also used to suggest possible restructuring of sentences for better academic readability. After using this tool, the authors carefully reviewed and edited the content as needed, taking full responsibility for the final text and ensuring that the intellectual contributions, interpretations, and conclusions are entirely their own.

Conflict of Interest

We confirm that the article is the original creation of the researcher. The article has not been published previously and is not currently being considered for publication by any other entity. This study has not been submitted for publication nor has it appeared in full or in part anywhere else. We attest that all Authors have made significant contributions to the work being submitted to the Journal of Creative Practices in Language Learning and Teaching (CPLT).

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Authors' Contributions

The writer composed this paper and utilized ChatGPT to enhance the final version.