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General and Technical Vocabulary as Predictors of ESP Reading Performance among Engineering Students at ENSAM Meknes

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ABSTRACT

This study examined whether general vocabulary knowledge and engineering-related technical vocabulary knowledge predict ESP reading performance among third- and fourth-year engineering students at ENSAM Meknes. The study was designed for a pooled engineering sample drawn from three majors and relied on a standardized measure of general vocabulary knowledge together with two researcher-developed instruments: a shared engineering-related technical vocabulary test and a shared engineering-ESP reading test. The design was motivated by two strands of scholarship. First, research on L2 reading has repeatedly shown that vocabulary knowledge is strongly associated with reading comprehension and that lexical coverage in a text affects how successfully readers construct meaning. Second, work on specialized discourse has argued that technical vocabulary should be identified in relation to the discourse practices of a field rather than treated as undifferentiated general lexis. The study used a cross-sectional predictive correlational design. General vocabulary knowledge was measured through the Updated Vocabulary Levels Test (UVLT), while engineering-related technical vocabulary knowledge and ESP reading performance were assessed through a 30-item vocabulary test and an 18-item reading test aligned with a shared engineering-ESP context. Both lexical predictors significantly contributed to ESP reading performance, but engineering-related technical vocabulary emerged as the stronger predictor in both hierarchical regression orderings. A commonality analysis further suggested that a substantial portion of the explained variance was shared by the two lexical predictors, while technical vocabulary retained the larger unique contribution. The overall pattern supports a layered view of ESP reading in which broad lexical knowledge provides an important base, but specialized vocabulary adds substantial explanatory value in discipline-oriented reading tasks.

INTRODUCTION

Vocabulary knowledge occupies a central position in second-language reading. Readers who know a larger proportion of the words in a text are generally better able to move beyond lexical decoding and allocate cognitive resources to inference, integration, and discourse-level interpretation. This principle has been confirmed repeatedly in applied linguistics, including studies showing strong links between vocabulary knowledge and academic reading performance and work demonstrating that reading comprehension is sensitive to lexical coverage in a text. In much of this literature, around 95% lexical coverage is treated as a lower threshold for workable comprehension, while 98% is often presented as a more secure threshold for fuller understanding.

In English for Specific Purposes (ESP), however, the lexical issue is more complex than in general EFL reading. Specialized texts do not merely contain more words; they contain words that function in field-sensitive ways. Engineering discourse, for example, relies not only on common academic language but also on vocabulary used to describe structures, tolerances, systems, constraints, failure, optimization, measurement, monitoring, and control. As a result, a study of reading in an engineering ESP context should distinguish between general vocabulary knowledge and technical vocabulary knowledge rather than collapse them into a single lexical construct.

The present article is built around that distinction. It examines third- and fourth-year students at ENSAM Meknès from Mechanical Engineering, Civil Engineering, and Artificial Intelligence, and asks whether general vocabulary knowledge and engineering-related technical vocabulary knowledge predict ESP reading performance. More precisely, it investigates whether technical vocabulary explains additional variance beyond what is already accounted for by a standardized measure of general vocabulary knowledge.

Conceptually, the study is important because it addresses a recurrent weakness in vocabulary-and-reading research within ESP: the tendency to rely on one broad lexical measure and then interpret the resulting correlation as if it captured the full lexical demands of disciplinary reading. Methodologically, the study is useful because it combines a standardized general-vocabulary measure with a researcher-developed technical-vocabulary measure and then analyzes both through hierarchical regression and commonality analysis. Pedagogically, the study matters because if technical vocabulary emerges as a stronger predictor, then engineering ESP courses may

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need to integrate more systematic lexical work directly into reading instruction.

LITERATURE REVIEW

Vocabulary knowledge and reading comprehension

The relationship between vocabulary knowledge and reading comprehension is one of the most stable findings in second-language acquisition research. Qian argued that vocabulary knowledge is centrally implicated in academic reading performance, while Schmitt, Jiang, and Grabe showed that comprehension changes in meaningful ways as the percentage of words known in a text changes. These studies support the broader claim that any credible account of reading performance must take vocabulary knowledge seriously. This relationship has also been observed in the local engineering ESP context, where Azalmad (2023) found that both vocabulary size and vocabulary depth were significantly associated with reading performance among ENSAM Meknes engineering students, with vocabulary depth emerging as the stronger predictor.

The lexical-threshold literature sharpens this relationship by showing that comprehension becomes increasingly difficult when a reader knows too small a proportion of the words in a text. Laufer and Ravenhorst-Kalovski revisited the threshold question and linked lexical text coverage, vocabulary size, and comprehension more explicitly. In ESP, this issue becomes especially pressing because specialized texts frequently increase lexical density and introduce field-sensitive vocabulary that may not be captured by ordinary general-language tests.

General vocabulary knowledge and the UVLT

A major strength of the present design is the use of the Updated Vocabulary Levels Test (UVLT) as the measure of general vocabulary knowledge. Webb, Sasao, and Ballance developed and validated the UVLT as a receptive test covering five frequency levels from 1,000 to 5,000. Unlike a purely global size estimate, the UVLT is useful for showing how securely learners control vocabulary across major frequency bands. In the present study, this makes the UVLT an appropriate baseline indicator of broad lexical knowledge.

Using the UVLT is also methodologically important because it prevents the technical-vocabulary measure from standing in for overall English proficiency. If one wants to claim that specialized vocabulary explains something distinctive about reading in an engineering context, then one must first account for a more general lexical base with a recognized instrument.

Technical vocabulary and engineering ESP

Technical-vocabulary research suggests that specialized lexical knowledge cannot be reduced to general word knowledge. Chung and Nation showed that technical vocabulary can make up a substantial proportion of specialized texts and argued that such vocabulary should be identified according to its role in disciplinary discourse. Their work is particularly relevant here because it shifts the focus from isolated words to words as they function in specialized meaning-making systems.

In engineering English, this insight becomes especially important. Engineering texts repeatedly draw on vocabulary related to systems, structures, failure, tolerancing, modeling, simulation, prediction, reliability, materials, and measurement. Ward's engineering English word-list research further supports the existence of a recurring lexical core relevant to engineering students. For that reason, the technical-vocabulary instrument used in this study was conceived not as a highly narrow sub-disciplinary tool, but as a shared engineering-related measure capable of functioning across the three participating majors.

Vocabulary assessment, overlap, and predictor interpretation

Once general and technical vocabulary are both included in the same study, a statistical challenge appears immediately: the two constructs are related and therefore likely to be correlated. Ordinary correlations cannot tell us how much each predictor contributes uniquely to reading once the other predictor is already in the model. Hierarchical regression helps resolve this problem because it allows theory-driven predictor ordering and makes it possible to test the incremental contribution of each variable.

Commonality analysis is particularly useful in this context because it decomposes the explained variance in the regression model into unique and shared components. This makes it possible to distinguish what general vocabulary explains uniquely, what technical vocabulary explains uniquely, and what both predictors explain together. In studies where predictors overlap conceptually, that decomposition often yields a more meaningful interpretation than standardized beta weights alone.

Research Questions and Hypotheses

The present study addresses the following research questions:

1. To what extent does general vocabulary knowledge predict ESP reading performance among ENSAM Meknès engineering students?
2. To what extent does engineering-related technical vocabulary knowledge predict ESP reading performance?
3. Does engineering-related technical vocabulary knowledge explain additional variance in ESP reading performance after general vocabulary knowledge has been taken into account?

The study advances three corresponding hypotheses.

H1: general vocabulary knowledge will significantly predict ESP reading performance.

H2: engineering-related technical vocabulary knowledge will significantly predict ESP reading performance.

H3: technical vocabulary knowledge will explain significant additional variance beyond general vocabulary knowledge.

MATERIALS AND METHOD

Research design

The study adopted a cross-sectional predictive correlational design. The dependent variable was ESP reading performance. The two focal predictors were general vocabulary knowledge and engineering-related technical vocabulary knowledge. Year of study and major were entered as control variables because the sample included students from three majors and two academic levels. The overall design was intended to separate broad lexical knowledge from more specialized engineering-related lexical competence while keeping the outcome anchored in shared engineering discourse.

Participants

The selected sample consisted of 130 students enrolled at ENSAM Meknès: 55 from Mechanical Engineering, 43 from Civil Engineering, and 32 from Artificial Intelligence. All participants were in the third or fourth year of study. The three groups were pooled into one engineering-ESP sample because the instrument pack was built around one shared engineering-related technical vocabulary test and one shared engineering-ESP reading test rather than three fully separate major-specific instruments. This preserved construct coherence and kept the sample large enough for the planned regression analyses.

Instruments

Three instruments were used to operationalize the main constructs of the study: (a) the Updated Vocabulary Levels Test (UVLT) as the measure of general vocabulary knowledge, (b) a researcher-developed Engineering-Related Technical Vocabulary Test as the measure of specialized lexical knowledge, and (c) a researcher-developed Engineering-ESP Reading Test as the criterion measure of reading performance. The decision to combine one standardized vocabulary instrument with two context-specific instruments was methodological as well as theoretical. It allowed the study to separate broad receptive lexical knowledge from engineering-related lexical competence while keeping the reading outcome anchored in a shared engineering ESP context.

The general vocabulary instrument was the Updated Vocabulary Levels Test (UVLT) developed by Webb, Sasao, and Ballance (2017). The UVLT is a validated receptive measure organized across the 1,000, 2,000, 3,000, 4,000, and 5,000 word-frequency levels, with 30 items at each level and a total possible score of 150. In the present study, the official published form of the test was administered without modification, and scoring followed the published procedure of one point per correct response. Because the UVLT is a published standardized instrument, Appendix C provides the instrument reference, administration note, and scoring framework rather than a full reproduction of the test items.

The Engineering-Related Technical Vocabulary Test was a 30-item multiple-choice instrument developed for the present study to assess knowledge of engineering-related lexical items shared across Mechanical Engineering, Civil Engineering, and Artificial Intelligence. The design of the instrument was informed by Chung and Nation's (2003, 2004) work on technical vocabulary identification, by Read's (2000) principles of vocabulary test construction, and by Ward's (2009) work on engineering English lexis. Items were written to reflect engineering discourse recurrent across the three majors, including monitoring, structures, tolerancing, systems, modelling, maintenance, measurement, and control. Each item contained one target word or expression embedded in a short technical sentence followed by four options, with one correct response and three semantically plausible distractors. The total possible score ranged from 0 to 30.

ESP reading performance was measured through an 18-item multiple-choice Engineering-ESP Reading Test developed for this study. The test consisted of three technical passages of increasing density and abstraction, each followed by six items, for a total of 18 items. The passages focused on structural health monitoring for reinforced concrete bridges, tolerance stack-up and manufacturability in multi-component assemblies, and predictive maintenance with edge AI in smart manufacturing. These topics were selected because they are broad enough to be interpretable across the three participating majors while still retaining an engineering-specific discourse profile. The item set targeted more than factual recall: it was designed to measure main-idea recognition, inference, interpretation of technical relationships, rhetorical function, and meaning in context. The total possible score ranged from 0 to 18.

Both researcher-developed instruments were piloted before the main administration. The pilot was used to check timing, clarity, distractor plausibility, and initial internal consistency. Following the pilot, two reading items and three technical-vocabulary items were revised to improve clarity and discrimination. The resulting reliability coefficients in the pilot phase were acceptable (Reading Test $\alpha = .78$; Technical Vocabulary Test $\alpha = .81$), and the final main-study reliability estimates are reported in the Results section.

Pilot study

Before the main administration, the two researcher-developed instruments were piloted with 24 students from the same institutional environment who were excluded from the final sample. The pilot was used to examine timing, clarity, internal consistency, distractor quality, and early item discrimination. Two reading items and three technical-vocabulary items were revised after the pilot. No marked floor or ceiling effects were observed, and the timing was judged appropriate for upper-level engineering students in an ESP setting.

Procedure

The study was structured around one administration cycle using the same sequence indicated in the instrument pack: UVLT first, then the technical vocabulary test, and finally the engineering-ESP reading test. This sequencing was selected to minimize the possibility that exposure to the reading passages would influence performance on the specialized-vocabulary measure. Students completed the instruments under classroom testing conditions, and demographic information including major and year of study was collected for analysis. Participation was voluntary, informed consent was obtained from all participants before data collection, and responses were anonymized prior to analysis.

Data analysis

The analysis proceeded in four stages. First, descriptive statistics and reliability estimates were computed for each instrument. Second, Pearson correlations were calculated among the main variables. Third, hierarchical multiple regression was conducted in two orderings: controls → UVLT → technical vocabulary, and controls → technical vocabulary → UVLT. Fourth, commonality analysis was used to partition the lexical contribution to reading performance into unique and shared variance. This sequence was chosen because the predictors were expected to overlap conceptually and statistically.

RESULTS AND DISCUSSION

Pilot study and instrument functioning

The pilot study showed that both researcher-developed instruments functioned satisfactorily before revision. The engineering-ESP reading test yielded Cronbach's α = .78, while the technical vocabulary test yielded Cronbach's α = .81. Two reading items and three vocabulary items were revised to improve semantic precision, distractor plausibility, and item discrimination.

After revision, both instruments appeared suitably challenging for the target group. This was important because the study was designed to assess performance in a genuine engineering-ESP context rather than to reproduce a general EFL testing situation. In practical terms, the pilot suggested that the measures captured meaningful variation without producing widespread failure or near-ceiling performance.

Table 1: Descriptive statistics and internal consistency estimates.

Measure	Possible score	Mean	SD	Min	Max	Reliability
UVLT total score	0–150	93.84	15.41	58	128	α = .91
Technical vocabulary test	0–30	18.72	4.58	8	28	α = .86
ESP reading test	0–18	11.34	2.96	4	17	α = .82

Note. UVLT = Updated Vocabulary Levels Test.

Descriptive interpretation

The descriptive pattern suggests that the sample occupied a plausible intermediate-to-upper-intermediate ESP profile. The UVLT produced the strongest reliability, as expected for a standardized instrument, while the two researcher-developed measures also performed satisfactorily after piloting. The mean reading score indicates that the participants were able to engage with the passages but still displayed enough variation for the predictive model to detect meaningful individual differences.

In a study of this kind, that spread is crucial. If the measures cluster too closely near the top or bottom, the relationship between vocabulary and reading becomes difficult to interpret. The score distribution reported here avoids that problem and allows the later regression model to function in a realistic way.

Correlation analysis

Pearson correlations among the main variables are presented in Table 2. Both lexical predictors were positively and significantly associated with ESP reading performance, but technical vocabulary showed the stronger bivariate relationship.

Table 2: Correlation matrix for the main variables

Variable	1	2	3	4
1. Year of study	—			
2. UVLT total score	.14	—		
3. Technical vocabulary	.11	.62***	—	
4. ESP reading performance	.16	.58***	.67***	—

*Note. *** $p < .001$. The overlap between UVLT and technical vocabulary justified the use of commonality analysis in addition to hierarchical regression.*

The correlation matrix shows three things clearly. First, both lexical measures are positively associated with reading, which reinforces the broad literature on vocabulary and comprehension. Second, the technical-vocabulary measure is more strongly related to the reading outcome than the UVLT in bivariate terms. Third, the two predictors overlap meaningfully with one another, but not to the point of redundancy.

This third point matters because it suggests that the two measures are not simply duplicates. They appear to share a general lexical foundation, while still capturing distinct aspects of lexical competence. That overlap-and-distinction pattern is precisely what the regression and commonality analyses were designed to explore.

Hierarchical multiple regression

A hierarchical regression was conducted with year of study and major entered first as controls, followed by the lexical predictors in alternating orders. Table 3 reports the first ordering in which the UVLT was entered before technical vocabulary.

Table 3: Hierarchical regression: controls → UVLT → technical vocabulary

Model	Predictors entered	R^2	Adjusted R^2	ΔR^2	F change	p
1	Year + Major	.08	.06	—	3.65	.014
2	+ UVLT	.37	.35	.29	57.54	< .001
3	+ Technical vocabulary	.50	.48	.13	32.28	< .001

Note. Major was dummy-coded, with Mechanical Engineering treated as the reference category.

In Model 1, year and major explained a modest but non-trivial proportion of the variance in reading performance. Once UVLT scores were entered, explained variance increased sharply from .08 to .37, indicating that general vocabulary knowledge made a substantial contribution to engineering-ESP reading. When technical vocabulary was added in the final step, total explained variance rose to .50, and the increase remained statistically significant. This means that technical vocabulary explained additional variance beyond year, major, and general vocabulary knowledge.

The final coefficients for Model 3 are shown in Table 4.

Table 4: Final regression coefficients for Model 3

Predictor	B	SE B	β	t	p
Constant	2.14	1.08	—	1.98	.050
Year of study	0.38	0.28	.09	1.36	.176
Civil vs Mechanical	-0.31	0.32	-.06	-0.95	.342
AI vs Mechanical	0.48	0.31	.10	1.57	.118
UVLT total score	0.05	0.01	.28	3.34	.001
Technical vocabulary	0.29	0.05	.46	5.68	< .001

Note. β = standardized regression coefficient.

In the final model, both lexical predictors remained statistically significant, but technical vocabulary emerged as the stronger predictor (β = .46) relative to general vocabulary (β = .28). The control variables were no longer significant once the lexical measures were taken into account. In interpretive terms, this suggests that

Table 5: Mirrored hierarchical regression: controls → technical vocabulary → UVLT

Model	Predictors entered	R^2	Adjusted R^2	ΔR^2	F change	p
1	Year + Major	.08	.06	—	3.65	.014
2	+ Technical vocabulary	.45	.43	.37	84.10	< .001
3	+ UVLT	.50	.48	.05	12.40	.001

Note. The mirrored model tests the incremental contribution of general vocabulary after technical vocabulary has already entered the equation.

the observed differences in reading performance were better explained by lexical competence than by major membership or year of study per se.

To test whether this pattern depended simply on entry order, the mirrored model was also estimated.

The mirrored model confirmed the same substantive result. When technical vocabulary entered first, it explained 37% additional variance beyond the controls. When the UVLT was then added, it contributed a smaller but still significant 5% additional variance. This comparison suggests that technical vocabulary made the larger unique contribution in the dataset.

Commonality analysis

Because the two lexical predictors were correlated, commonality analysis was used to partition their contribution to reading performance into unique and shared components.

The commonality analysis indicates that the lexical block explained 42% of the variance in reading after the control variables were partialled out. The largest component was the shared variance between general and technical vocabulary, which suggests that the strongest readers combined a broader lexical base with stronger engineering-related lexical knowledge.

Table 6: Commonality analysis of lexical predictors

Variance component	Proportion of total reading variance	Percentage of lexical explained variance
Unique contribution of UVLT	.05	11.9%
Unique contribution of technical vocabulary	.13	31.0%
Shared contribution of UVLT + technical vocabulary	.24	57.1%
Total lexical contribution	.42	100%

Note. The lexical block explained 42% of the variance in reading performance after the control variables were partialled out.

At the same time, the unique contribution of technical vocabulary was more than double that of the UVLT. This is theoretically important because it suggests that specialized lexical competence was not merely borrowing its predictive value from general English knowledge. Rather, it retained a substantial distinct role in accounting for differences in engineering-ESP reading performance.

Assumption checks

Standard diagnostics suggested that the regression model was stable. Residual plots indicated acceptable linearity and homoscedasticity, the normal probability plot suggested no serious deviation from normality, and multicollinearity did not appear problematic. Variance inflation factors ranged from 1.18 to 1.84, indicating that the overlap between the two lexical predictors did not compromise the interpretability of the coefficients.

Summary of findings

Overall, the results support three main conclusions. First, both general vocabulary knowledge and engineering-related technical vocabulary knowledge significantly predicted ESP reading performance. Second, technical vocabulary emerged as the stronger predictor in both hierarchical orderings. Third, the commonality analysis indicated that the lexical influence on reading was partly shared and partly specialized, with technical vocabulary retaining the larger unique contribution.

Discussion

The purpose of this study was to examine whether general vocabulary knowledge and engineering-related technical vocabulary knowledge predict ESP reading performance among ENSAM Meknès engineering students. The findings suggest that both lexical dimensions matter, but they do not matter equally. Broad vocabulary knowledge made a substantial contribution to reading, which is fully in line with the long-established literature linking vocabulary and reading comprehension. At the same time, technical vocabulary emerged as the stronger unique predictor, indicating that specialized lexical knowledge adds something important beyond a general lexical base. This pattern is broadly consistent with Azalmad's (2023) findings in the same institutional environment, where vocabulary depth outperformed vocabulary size as a predictor of reading performance among ENSAM Meknes engineering students.

This finding is theoretically meaningful for ESP. If the UVLT had accounted for nearly all of the lexical effect, one might conclude that engineering-ESP reading is largely just a reflection of general English proficiency. The pattern reported here suggests something more nuanced. General vocabulary remains indispensable, but technical vocabulary appears to provide additional access to the meanings and relations encoded in engineering discourse. That interpretation aligns well with technical-vocabulary research, which argues that specialized texts depend on lexical items whose disciplinary relevance cannot be fully captured by general vocabulary measures.

The commonality analysis strengthens that interpretation. More than half of the lexical contribution to reading was shared by the two predictors, which suggests that the strongest readers were not simply students who had memorized more technical terms in isolation. Rather, they were students who combined a relatively strong general lexical base with stronger engineering-related vocabulary knowledge. This shared component is important because it reminds us that specialized vocabulary does not operate in a vacuum. It is built on, and interacts with, broader lexical competence. At the same time, the larger unique contribution of technical vocabulary indicates that specialized lexical knowledge is not reducible to general English knowledge.

Pedagogically, the findings point toward a two-layer lexical approach to ESP reading instruction at ENSAM Meknès. Students still need development in general academic and high-frequency vocabulary, since that knowledge supports text processing globally. But they also need systematic work on engineering-related technical vocabulary, especially the lexis that appears repeatedly in system description, monitoring, measurement, design constraints, reliability, optimization, and process explanation. In other words, technical vocabulary should not be treated as an optional glossary appended to content work; it should be integrated into reading instruction as one of the mechanisms through which learners make sense of specialized texts.

The study also offers a methodological contribution. Many vocabulary-reading studies in applied linguistics rely on one broad lexical measure and then correlate it with reading performance. That approach is informative, but it cannot distinguish how much of the reading outcome is tied specifically to specialized lexical competence. By combining a standardized general-vocabulary measure with a researcher-developed technical-vocabulary test and then analyzing their overlap through hierarchical regression and commonality analysis, the present design offers a more differentiated account of lexical influence in ESP reading.

At the same time, the study should be interpreted within its limits. First, the pooled design treats Mechanical Engineering, Civil Engineering, and Artificial Intelligence as members of one shared engineering-ESP context, which is defensible for the present instrument set but does not capture possible major-specific lexical differences in full detail. Second, the technical-vocabulary instrument, although aligned with ESP theory, remains researcher-developed rather than fully standardized.

These limitations do not weaken the conceptual value of the article, but they define the next empirical steps clearly. Later studies could also examine whether the relative weight of technical vocabulary differs across majors or whether growth in technical vocabulary over time predicts growth in reading performance more strongly than general vocabulary growth alone.

CONCLUSION

This article examines the relationship between general vocabulary knowledge, engineering-related technical vocabulary knowledge, and ESP reading performance among third- and fourth-year ENSAM Meknès students. Both lexical predictors were significant, but they did not contribute equally. General vocabulary knowledge provided a substantial explanatory base, while technical vocabulary emerged as the stronger predictor and retained the larger unique contribution once the overlap between the two lexical dimensions had been taken into account.

The broader implication is that reading in engineering ESP contexts should not be explained through a single undifferentiated notion of vocabulary. A more accurate account is layered: broad lexical competence supports reading generally, while specialized vocabulary adds substantial interpretive power when students engage with technical discourse.

For teaching, that means vocabulary instruction in engineering ESP should move beyond general word learning and incorporate systematic work on recurring engineering-related lexis. For research, it means that models of ESP reading should distinguish more carefully between general and specialized lexical knowledge rather than allowing one to stand in for the other.

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