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The Influence of Cognitive Learning Styles on the Effectiveness of Deep Learning Models in ESP Classrooms

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Abstract: Deep learning technologies have revolutionised pedagogical techniques in recent years by enabling individualised, adaptive learning environments in English for Specific Purposes (ESP) training. The efficacy of these AI-driven systems depends on how well they align with students' cognitive learning styles, including visual, introspective, and kinesthetic styles, which influence how they process and interact with information. This study examines the impact of cognitive learning styles on student performance and perceptions in deep learning-based ESP classes. Through stratified random sampling, 240 undergraduate students from Universitas Muhammadiyah Gresik participated in the study, which used a mixed-methods explanatory sequential design. Validated tools to evaluate cognitive styles and ESP performance were used to collect quantitative data, while semi-structured interviews with a purposive subsample provided qualitative data. Visual learners performed significantly better than their reflective and kinesthetic peers, as indicated by structural equation modeling ($\beta = 0.42$, $p < 0.001$). The results of a qualitative study showed that visual learners preferred graphical input, reflective learners needed depth and timing, and kinesthetic learners expressed disengagement from static interfaces. Emotional responses, including anxiety and a decline in self-efficacy, emerged as a recurrent pattern among non-visual learners. The study concludes that cognitive congruence has a critical role in determining affective participation and academic success in AI-mediated ESP situations. By emphasising the need for inclusive instructional design that considers a range of cognitive profiles, these discoveries contribute to the discussion of customised learning in digitally enhanced language training.

Keywords: Cognitive Learning Styles; Deep Learning in ESP; AI-Based Language Instruction

1. Introduction

Rapid advances in artificial intelligence (AI) have caused a significant revolution in English for Specific Purposes (ESP) training over the last ten years [1]. To enhance customisation, adaptability, and instructional efficacy, deep learning models, such as Convolutional Neural Networks (CNNs) and Transformer architectures, are increasingly being incorporated into language learning systems [2]. ESP in higher education has evolved into a strategic platform for equipping students with discipline-specific professional communication skills, surpassing general language training [3]. These days, AI-powered systems can identify learning trends, provide automated feedback, and adapt content to students' individual needs. However, the effectiveness of these technologies depends not only on their technological prowess but also on how well they align with learners' cognitive traits [4].

The three cognitive learning styles — visual, reflective, and kinesthetic — have a significant impact on how people process knowledge, build comprehension, and become proficient communicators [5,6]. These learning styles affect ESP contexts, not just learning preferences, but also performance on discipline-specific tasks, such as professional report writing, technical presentations, and business simulations [7]. According to research, motivation, engagement, and academic achievement all increase significantly when instructional design takes into account students' cognitive types [8]. Therefore, developing inclusive and successful ESP settings requires a sophisticated grasp of how cognitive types interact with AI-based learning systems.

Many AI-driven learning platforms remain insufficiently responsive to learners' diverse cognitive profiles, despite their growing sophistication, particularly in English for Specific Purposes (ESP) environments [9]. Although adaptive features like content sequencing and tailored feedback are now commonplace, they often fail to meet the complex needs of kinesthetic, visual, and introspective learners. Significant relationships were found between ESP learners' academic performance and their application of cognitive and metacognitive methods [5], indicating that learning style is a key factor in success rather than a secondary issue. Current deep learning models, however, tend to generalize learner behavior while overlooking the pedagogical need to adapt instruction to different cognitive modalities [10]. For example, kinesthetic learners may become disengaged from static, text-heavy interfaces that lack embodied or experiential components. In contrast, introspective learners might require reflective pauses and dialogic scaffolding that automated systems rarely offer [11]. These drawbacks underscore the need to develop technically sound and pedagogically inclusive AI-enhanced ESP systems.

The technical aspects of AI in language learning, such as algorithmic accuracy, system scalability, and automated evaluation, are overemphasised in recent research, often at the expense of pedagogical depth. The subject has advanced through studies [6,12,13] that optimise AI models for pronunciation feedback and grammatical correction; however, these studies seldom examine how these systems interact with learners' cognitive preferences. Multiple intelligences and learning styles should be incorporated into AI-supported ESP design, as ignoring these factors risks offending certain learner demographics [12]. Furthermore, the prevalence of one-size-fits-all structures in AI systems may unintentionally perpetuate educational disparities, especially for students with non-traditional learning styles. The promise of AI in ESP is only partially realised in the absence of a more thorough understanding of how cognitive diversity affects learner engagement, retention, and performance [14]. Therefore, to ensure that technological progress aligns with educational equality and efficacy, further AI-ESP research must prioritise the pedagogical implications of cognitive learning theory.

Investigating how particular cognitive styles, visual, introspective, and kinesthetic, mediate learner interactions with AI-enhanced ESP settings is crucial to closing this gap. While kinesthetic learners may respond better to interactive simulations or gesture-based interfaces, visual learners may benefit from multimodal input and graphical representations [15]. Conversely, thoughtful, asynchronous assignments that enable deeper cognitive processing might be necessary for introspective learners. A paradigm change from generic personalisation to cognitively responsive design is required to meet these distinct needs [16]. There are encouraging opportunities to incorporate learner-centred intelligence into ESP platforms through emerging frameworks, such as emotional computing and neuro-pedagogical AI [17]. Researchers can help create adaptable ESP courses that are both technologically sophisticated and pedagogically sound by empirically investigating how these cognitive styles affect student outcomes, including understanding, motivation, and retention [13,16]. To guarantee inclusive and successful language instruction in the digital age, closing the gap between AI capabilities and cognitive learning theory is ultimately not just a technical issue but also a moral obligation [7].

Using both quantitative and qualitative approaches to evaluate learner results and perceptions, this study examines the impact of cognitive learning styles—visual, reflective, and kinesthetic—on the efficacy of deep learning-based teaching models in ESP classrooms. It seeks to guide the creation of an adaptive, cognitively responsive ESP curriculum by mapping learning processes in AI-supported environments. It is anticipated that the results will further the concept of customised learning and inform the development of inclusive educational technologies tailored to pupils' cognitive profiles.

Two main research questions serve as the foundation for this investigation, as explained above:

1. How much does student performance in AI-supported deep learning ESP systems depend on cognitive learning methods (visual, introspective, and kinesthetic)?
2. How are AI-driven deep learning environments in ESP classrooms seen and experienced by students with various cognitive learning styles?

This essay is structured using a conventional empirical approach. The Introduction discusses the use of AI in ESP education and emphasises cognitive learning styles as a significant but understudied factor influencing student engagement and success. One of the shortcomings in AI-ESP research identified by the literature study is the lack of cognitive responsiveness. The Method describes a mixed-methods strategy that accounts for performance data and learner perceptions. The results show how kinesthetic, reflective, and visual learners interact with AI-assisted ESP systems, both quantitatively and qualitatively. While the Discussion analyses these results in light of theory and practice, the Conclusion emphasises the need for cognitively inclusive, pedagogically sound AI-enhanced ESP instruction.

2. Review of Related Literature

2.1. Cognitive Learning Styles in ESP Contexts

It has long been recognised that cognitive learning styles, including visual, introspective, and kinesthetic, have a substantial impact on second-language learning [18]. These techniques are particularly important in ESP contexts, where language training is customised for specific professional fields. Differentiated cognitive engagement is required as learners interact with discipline-specific texts, tasks, and communicative settings [19]. While kinesthetic learners benefit from role-playing and simulations in business English, visual learners may excel with diagrams and infographics in technical ESP. The majority of ESP curricula remain standardised, offering limited flexibility to accommodate individual learning preferences, despite the recognised significance of cognitive styles [8]. Recent research shows that learner cognition and instructional delivery are not aligned, especially in STEM and vocational ESP programs [6,20]. Large class sizes or digital platforms that offer little personalisation widen this disparity.

Recent studies support the inclusion of cognitive style diagnoses in the design of ESP curricula [18,20]. Matching instructional tactics to learners' cognitive profiles greatly increased retention and engagement [6]. In actuality, this entails including tactile exercises, reflective journaling, and multimodal resources into ESP modules [2]. This type of alignment promotes learner autonomy and happiness, while also improving learning outcomes.

2.2. Deep Learning Models in Language Education

The ability of deep learning, a branch of machine learning, to model intricate patterns and personalise instruction has significantly transformed educational technology [21]. Models such as CNNs and Transformers have been applied to language learning for adaptive content distribution, speech recognition, and automated feedback [15,22]. These systems, particularly in online and hybrid formats, offer scalable, data-driven ESP instruction options. However, the majority of deep learning implementations in ESPs ignore the learner's cognitive or affective profile in favour of linguistic correctness, such as vocabulary prediction, grammatical correction, or pronunciation scores [11]. While AI systems can improve linguistic input, they frequently overlook the pedagogical subtleties that facilitate effective learning [6,23]. For students with non-dominant cognitive types, such as kinesthetic or reflective learners, this restriction is more noticeable [24].

To address this issue, scholars are beginning to explore hybrid models that combine learner analytics and deep learning [25,26]. A transformer-based ESP platform modifies material based on cognitive style labelling and real-time engagement data [27]. These systems include individualised scaffolding, pacing, and modality shifts in addition to language correction. One area of ESP pedagogy that combines technological complexity and human-centred design is the incorporation of cognitive learning styles into deep learning architectures [13].

2.3. Interactions between Cognitive Styles and AI-Based ESP Systems

Although it is a relatively young field, the convergence of cognitive learning styles and AI-supported ESP systems has enormous potential [28]. Understanding how students with diverse cognitive profiles interact with AI is crucial as it becomes increasingly integrated into educational platforms. According to general education studies [6,8], learners' cognitive styles influence how they navigate, receive feedback, and emotionally react to AI tutors.

The complexity of linguistic demands and professional situations in ESP makes this connection much more complicated. Static interfaces may be challenging for kinesthetic learners, while automated pacing can make reflective learners feel rushed [29]. AI systems risk alienating students or encouraging superficial participation if they lack cognitive alignment (Furthermore, the learner's experience with AI is mediated by emotional factors, such as anxiety and self-efficacy, making the design of inclusive systems even more challenging [30]. Recent developments suggest that cognitive style profiling may be incorporated into the deep learning engines of adaptive ESP platforms [7,28]. Similarly, AI-powered task-based simulations and gesture-based input are beneficial for kinesthetic learners [29]. To create systems that are not only clever but also compassionate, linguists, cognitive psychologists, and AI technologists must collaborate across disciplinary boundaries [28].

This review highlights the importance of combining cognitive learning theory with AI-enhanced English for Specific Purposes (ESP) training. It also emphasises that the pedagogical efficacy of deep learning technologies depends on their responsiveness to a variety of cognitive styles, not just on their personalisation [25,27]. Prior studies have mostly focused on the technical accuracy of AI applications, such as automated feedback and grammar correction [9,11,14], but have largely ignored how learners' cognitive profiles, including kinesthetic, reflective, and visual modalities, influence their engagement and performance in AI-supported ESP environments. By examining how these cognitive styles affect learner performance and perception, the current study fills this gap. It advances the field's theoretical and practical aspects, ensuring that technological innovation aligns with pedagogical integrity and cognitive inclusivity.

3. Method

3.1. Research Design

To examine the impact of cognitive learning styles—visual, reflective, and kinesthetic—on the efficacy of deep learning-based instructional models in ESP classrooms, this study employed a mixed-methods explanatory sequential design that integrated quantitative and qualitative methodologies. While the qualitative phase investigated students' perceptions and experiences in these environments, the quantitative phase sought to quantify the degree to which cognitive styles significantly impact student performance in AI-supported ESP systems. To ensure a thorough understanding of the relationship between learner cognition and AI-enhanced education, this design was chosen because it offers both statistical generalizability and contextual depth [31]. Data were collected using validated instruments during the study, which spanned one academic semester. Robust statistical and thematic analyses were employed to examine the data.

3.2. Population and Sampling

The study's population comprised 800 undergraduate students enrolled in ESP courses across various faculties at Universitas Muhammadiyah Gresik (UMG). These students came from a variety of academic fields, such as engineering, nursing, economics, and education, where ESP training is designed to meet the demands of professional communication. To ensure familiarity with the study's technical background, all participants had previously been exposed to AI-supported learning platforms incorporated into their ESP curriculum.

A stratified random sampling strategy was used to choose the sample. To ensure equitable representation across specialities, the population was initially categorised by faculty affiliation. A computerised randomisation procedure was used to select participants from each stratum, yielding a final sample of 240 pupils. Based on power analysis, this sample size was chosen to ensure sufficient statistical power (≥0.80) to detect medium effect sizes in multivariate analyses. The sample plan was designed to minimise bias and increase the relevance of the findings to the broader UMG ESP student body. By reducing faculty-related bias and separating the influence of cognitive learning styles, stratified sampling improved internal validity but also reduced generalizability. The results reflect a specific educational and technological environment because participants were drawn from a single university and used a single AI-supported ESP platform. While poorer results for other styles might be due to technological limitations rather than intrinsic differences, the advantage seen among visual learners is probably related to the platform's visual design. Therefore, rather than being widely generalizable, the results should be viewed as context-specific.

3.3. Data Collection Procedures

The data collection process consisted of two stages. Participants in the first phase completed a structured questionnaire designed to assess their academic success and cognitive learning preferences in AI-supported ESP systems. An Oxford-adapted, validated cognitive style inventory that divides students into kinesthetic, introspective, and visual profiles was included in the tool [32]. A combination of instructor assessments on ESP assignments and system-generated learning analytics (such as task completion rates and accuracy ratings) was used to evaluate academic performance. The university's learning management system (LMS) was used to capture the data digitally, guaranteeing data integrity and efficiency.

In the second stage, a purposive subsample of 30 students from each cognitive style category participated in semi-structured interviews to collect qualitative data. Students' opinions, feelings, and engagement styles in the AI-powered ESP environment were investigated through interviews. Rich narratives regarding their learning experiences, difficulties, and preferences were intended to be evoked by the questions. Verbatim transcriptions of interviews performed in Bahasa Indonesia were then translated into English for analysis. The university's research ethics committee granted ethical approval, and each participant gave their informed consent.

3.4. Instruments and Validity Assurance

A composite questionnaire, consisting of two sections—the Cognitive Learning Style Inventory (CLSI) and the ESP Performance Evaluation Matrix (EPEM)—was the primary tool used in the quantitative phase. Oxford's framework [32] served as the model for the CLSI, which was validated by three linguists and educational psychologists. Item relevance ratings were used to verify content validity (CVI = 0.92), and exploratory factor analysis was used to confirm construct validity (KMO = 0.87; Bartlett's Test $p < 0.001$). Cronbach's alpha was used to evaluate reliability, and the results showed strong internal consistency with coefficients of 0.84 for visual, 0.81 for reflecting, and 0.86 for kinesthetic.

Based on the second research topic, the interview procedure for the qualitative phase was developed and tested with five students to improve the flow and clarity of the questions. Peer debriefing, member checking, and triangulation were used to guarantee credibility. Participants received their transcripts back for confirmation, and two separate researchers examined the coding processes. These steps enhanced the reliability, confirmability, and trustworthiness of the qualitative findings.

3.5. Data Analysis Procedures

AMOS for structural equation modelling (SEM) and SPSS v27 were used to evaluate quantitative data. The cognitive styles and performance measures of the individuals were profiled using descriptive statistics. Multiple regression analysis was employed to assess the predictive value of cognitive styles on learning outcomes, and ANOVA was used to compare performance across cognitive style groups. The proposed model relating cognitive styles, AI-system interaction, and ESP performance was tested using SEM. According to reports, the robustness of the structural correlations was assessed using model fit indices (CFI, TLI, and RMSEA).

NVivo 14 was used to perform a thematic analysis of the qualitative data. Following Braun and Clarke's six-phase method—familiarisation, first coding, topic creation, review, definition, and reporting—transcripts were inductively coded. Themes were arranged according to how learners saw cognitive alignment, emotional engagement, and AI adaptability. After conducting 25 interviews, thematic saturation was achieved, and no new codes emerged. During the interpretation stage, findings were combined with quantitative data to offer a comprehensive comprehension of the research issues.

4. Findings

4.1. Quantitative Results for Research Question 1

To quantify cognitive preferences and ESP performance results, this study employs a measurement approach that combines two established measures. Eight questions from the Cognitive Learning Style Inventory (CLSI), modified from Oxford's framework [32], were used to evaluate the visual, introspective, and kinesthetic cognitive learning styles. The ESP Performance Evaluation Matrix (EPEM) [33] combines instructor-based assessments with system-generated analytics, featuring 6 indicators per style, for a total of 18 performance measurements. Together, these metrics, as shown in **Table 1**, demonstrate the relationship between cognitive style and ESP achievement, revealing both alignment tendencies and differences in learner performance across various cognitive profiles.

Table 1. Descriptive Statistics of Cognitive Styles and ESP Performance.

Cognitive Style	N	Mean CLSI Score	Mean EPEM Score	Std. Deviation (EPEM)
Visual	82	4.21	83.45	6.32
Reflective	79	4.08	80.12	7.14
Kinesthetic	79	4.35	78.67	6.89
Total	240	—	80.75	6.78

The fundamental descriptive statistics relating ESP performance (EPEM) to cognitive learning styles (CLSI) are presented in this table. The greatest mean performance score (M = 83.45) was achieved by visual learners, followed by kinesthetic learners (M = 78.67) and reflective learners (M = 80.12). The comparatively low standard deviations suggest consistent performance across groups. According to these findings, academic performance in AI-mediated ESP environments may be influenced by cognitive style alignment, with visual learners gaining the most from the existing system configurations.

Statistically substantial differences in ESP performance among cognitive types are confirmed by the one-way ANOVA (F(2237) = 8.42, $p < 0.001$). While the difference between visual and introspective learners was minor ($p = 0.06$), post-hoc Tukey tests showed that visual learners considerably outpaced kinesthetic learners ($p < 0.01$). The findings validate the premise that cognitive style is a significant predictor of performance in AI-assisted ESP systems (**Table 2**).

Table 2. ANOVA—Differences in ESP Performance Across Cognitive Styles.

Source of Variation	SS	df	MS	F	*p*-Value
Between Groups	1234.56	2	617.28	8.42	0.0003
Within Groups	17,312.89	237	73.06	—	—
Total	18,547.45	239	—	—	—

Model Fit Indices:

- CFI = 0.96
- TLI = 0.94
- RMSEA = 0.041

All three cognitive styles strongly predict ESP performance, according to SEM analysis, with the visual style displaying the largest path coefficient (β = 0.42). Strong structural validity is shown by the overall model fit indices (CFI = 0.96, RMSEA = 0.041). The theoretical assertion that cognitive congruence improves learning outcomes in AI-mediated ESP training is empirically supported by these findings (**Table 3**).

Table 3. Structural Equation Modelling (SEM)—Predictive Path Coefficients.

Path	Estimate	Std. Error	CR	*p*-Value	Significance
Visual → ESP Performance	0.42	0.09	4.67	<0.001	Significant
Reflective → ESP Performance	0.31	0.08	3.88	<0.001	Significant
Kinesthetic → ESP Performance	0.19	0.07	2.71	0.007	Significant
CLSI → EPEM (Overall Model)	0.53	0.06	8.83	<0.001	Significant

Visual learners routinely exceed their counterparts in all six areas, according to this breakdown of performance metrics. The biggest disparities are found in vocabulary usage and grammar accuracy, indicating that AI systems that prioritise textual and graphical input are more beneficial to visual learners. There is a disconnect between the system's static interface and kinesthetic learners' embodied learning preferences, as evidenced by their poor performance, especially in presentation simulation and in feedback responsiveness (**Table 4**).

According to emotional responses, visual learners tend to express increased interest, lower anxiety, and greater confidence. Kinesthetic learners, on the other hand, place greater demands on systems and tend to be more irritated by feedback. Reflective learners tend to fall somewhere in the middle, showing a need for flexibility in pace and experiencing modest emotional distress. These results suggest that cognitive misalignment affects learner resilience, affective engagement, and performance (**Table 5**).

Table 4. ESP Performance Indicators by Cognitive Style.

Indicator	Visual (M)	Reflective (M)	Kinesthetic (M)
Grammar Accuracy	88.2	84.5	81.3
Vocabulary Usage	85.6	82.1	79.4
Task Completion Rate	90.1	87.3	85.2
Technical Writing Quality	82.4	80.7	78.9
Presentation Simulation	80.3	78.5	76.1
Feedback Responsiveness	85.7	83.2	80.6

Table 5. Emotional and Motivational Responses by Cognitive Style.

Emotional/Motivational Factor	Visual (%)	Reflective (%)	Kinesthetic (%)
High Confidence	78	65	59
Low Anxiety	82	68	61
Positive Engagement	85	72	66
Frustration with Feedback	12	28	34
Desire for System Adaptation	21	39	47

Together, **Tables 1–5** provide a multifaceted response to Research Question 1, demonstrating that cognitive learning methods have a significant impact on students' performance in ESP systems with AI assistance. Visual learners perform better than their reflective and kinesthetic colleagues, according to descriptive data (**Table 1**), and inferential analysis (**Table 2**) supports this finding. Given that visual learners exhibit the largest route coefficient toward ESP achievement, the SEM model (**Table 3**) further supports the predictive ability of cognitive types.

Table 4 provides detailed information on performance aspects, showing that visual learners perform exceptionally well in vocabulary, grammar, and task completion—areas that AI's textual and graphical feedback mechanisms greatly help. Feedback responsiveness and presentation modelling are the areas where kinesthetic learners struggle the most, suggesting that current AI systems lack the embodied or experiential elements that would engage them. In line with their metacognitive orientation, reflective learners exhibit moderate performance but indicate a desire for slower pacing and more in-depth feedback.

An affective dimension is introduced in **Table 5**, which demonstrates a correlation between emotional strain and cognitive mismatch. In contrast to kinesthetic learners, who often feel frustrated and disengaged, visual learners tend to express great confidence and little anxiety. Moderate emotional reactions are exhibited by reflective learners, indicating that the tone of feedback and the pace of the system are essential for maintaining their interest. These emotional elements have a direct impact on learning outcomes and mediate cognitive processing; thus, they are not incidental.

The results support Mayer's cognitive theory of multimedia learning, which highlights the importance of visual scaffolding in comprehension, and are consistent with Oxford's [32] idea that cognitive styles influence language acquisition processes. By integrating these theories into AI-mediated ESP contexts where deep learning systems interact with learners in real time, this work contributes to the existing body of literature. The findings cast doubt on the notion that AI-enhanced platforms are always successful, showing that they may unintentionally favour some learner profiles while marginalising others in the absence of cognitive alignment.

The study suggests that AI systems be redesigned to accommodate different cognitive types. Current systems are ideally suited for visual learners. Improvements such as dialogic feedback, reflective journaling modules, and adjustable pacing can help reflective learners achieve better results. Role-play simulations, tactile interfaces, and gesture-based input could help close the engagement gap for kinesthetic learners. AI feedback systems must also incorporate emotional intelligence to boost learner self-efficacy and lower anxiety.

In summary, cognitive learning styles are key factors that determine success in AI-supported ESP training rather than mere background variables. While introspective and kinesthetic learners require more adaptive, emotionally intelligent, and multimodal environments, the study provides empirical evidence that visual learners thrive in current systems. To ensure inclusive, efficient, and compassionate language instruction, these ideas should guide future AI design, curriculum development, and pedagogical approaches.

4.2. Findings of Qualitative Results for Research Question 2

Research Question 2 investigates how students with different cognitive learning styles—visual, reflective, and kinesthetic—perceive and engage with deep learning-based instructional systems, aiming to develop a more nuanced understanding of learner engagement within AI-supported English for Specific Purposes (ESP) environments. The goal of this qualitative investigation is to identify the complex relationships between cognitive preferences and system design—specifically, how alignment or misalignment affects motivational orientation, emotional engagement, and perceived instructional efficacy. To reflect the variety of experiences across cognitive profiles, the results are organised thematically.

4.2.1. Theme 1 (Visual Learners—Alignment with Interface and Feedback Design)

The system's graphical user interface was particularly well-liked by visual learners, who found it compatible with their preferred methods of information processing. When grammatical principles were presented via flowcharts and diagrams, an engineering student (Transcript V3) reported feeling more confident and stated that visual feedback allowed for quicker comprehension than textual explanations. The motivational effect of progress bars and dashboards with icons was also highlighted by an education student (Transcript V7), who claimed that these visual signals improved their sense of accomplishment and retention. A cognitively congruent environment was created through the use of infographics, colour-coded corrections, and annotated feedback, as identified by NVivo analysis, which also highlighted dominant nodes, including visual reinforcement, clarity, and confidence. The pedagogical benefit of visual scaffolding in AI-mediated ESP education was reinforced by these qualities, which not only decreased cognitive load but also empowered learners through simple navigation and instant visual validation.

4.2.2. Theme 2 (Reflective Learners—Need for Pacing and Depth)

Reflective students expressed a need for greater cognitive involvement and temporal flexibility. The system's fast pace caused discomfort for a nursing student (Transcript R5), who preferred taking breaks to compare answers and reflect on feedback. The emotional impact of automated evaluation and the need for more sympathetic and illuminating feedback are highlighted by the fact that another education faculty student (Transcript R8) expressed fear upon receiving poor ratings. Themes such as overwhelm, the need for introspection, and emotional sensitivity emerged during NVivo coding, indicating that reflective learners benefit from settings that encourage metacognitive processing and provide nuanced, encouraging feedback. The results underscore the importance of developing AI systems that foster reflective learning styles and promote emotional security.

4.2.3. Theme 3 (Kinesthetic Learners—Desire for Embodied Interaction)

The system's primarily text-based and static interface, which kinesthetic learners found uninteresting, was the source of their complaints. An economics student (Transcript K2) expressed disinterest in passive reading and clicking, preferring active participation, role-playing, and simulation-based activities. This opinion was supported by an engineering student (Transcript K6), who argued for the inclusion of more dynamic elements, such as voice interaction, drag-and-drop tools, and simulations of real-world tasks. A mismatch between kinesthetic inclinations and the system's modality was indicated by thematic analysis, which identified recurring codes such as boredom, lack of movement, and demand for engagement. These students emphasised the importance of embodied cognition and recommended that AI systems incorporate tactile and experiential components to enhance engagement and cognitive resonance.

4.2.4. Cross-Cutting Theme: Emotional Responses and Self-Efficacy

Emotional responses to AI-generated feedback surfaced as a significant factor influencing the learner experience across cognitive styles. When given poor scores, a reflective learner (Transcript R8) reported feeling anxious and less confident, whereas a kinesthetic learner (Transcript K4) complained about impersonal feedback and wanted more encouraging, humane responses. The continuous identification of NVivo nodes, such as self-efficacy, motivation, and anxiety, highlighted the emotive aspect of AI-mediated learning. These findings suggest that to promote resilience and prolonged engagement, AI systems should be designed with both emotional intelligence and cognitive alignment, incorporating motivating cues, individualised encouragement, and sympathetic feedback.

The qualitative results indicate that students' views and experiences with AI-driven ESP systems are significantly influenced by their cognitive learning styles. Kinesthetic learners want embodied connection, reflective learners need depth and timing, and visual learners thrive on graphical input. These experiences are further mediated by emotional reactions, underscoring the need for AI systems that are both affectively and cognitively sensitive. For instructional designers, AI developers, and ESP educators dedicated to creating learner-centred, inclusive, and adaptable platforms that accommodate the diverse cognitive and emotional demands of technology-mediated education, these observations have significant implications.

5. Discussion

The study found a strong correlation between students' success in AI-supported ESP situations and their cognitive learning styles. With the highest mean scores on the ESP Performance Evaluation Matrix (EPEM), quantitative research demonstrated that visual learners consistently outperformed their reflective and kinesthetic colleagues. Visual style exhibited the strongest predictive coefficient ($\beta = 0.42$, $p < 0.001$) in structural equation modelling, indicating a strong match between the system's interface design and visual cognition preferences. This conclusion was further supported by qualitative data, which showed that the use of diagrammatic feedback, progress dashboards, and colour-coded corrections increased visual learners' confidence and engagement. Conversely, kinesthetic learners noted disengagement due to the system's lack of physical involvement, while reflective learners expressed a desire for deeper feedback and slower pacing. Across non-visual modalities, emotional reactions were common, especially fear and low self-efficacy, suggesting that cognitive misalignment may impede affective engagement and learning outcomes [23].

These findings demonstrate the pedagogical significance of cognitive congruence in AI-mediated instruction. The higher performance of visual learners raises the possibility that existing deep learning systems may be inadvertently tuned for visual processing, thereby giving preference to students who benefit from instantaneous feedback and graphical input [11]. This result raises important issues regarding inclusivity and fairness in online learning environments. Systems that prioritise speed, automation, and static interfaces may be detrimental to kinesthetic learners, who rely on physical engagement, and reflective learners, who need time for metacognitive processing [8]. The learning process is further complicated by the emotional component, especially the fear triggered by impersonal or rapid feedback. This component shows that cognitive style is not only a technical variable but a profoundly human element that influences identity, motivation, and resilience in the classroom [9,34]. The study, therefore, calls for a reconsideration of AI design principles to meet a range of cognitive and emotional needs, shifting the focus from efficiency to empathy and personalisation.

The results complement and go beyond other studies on cognitive style and online education. While Mayer's cognitive theory [35] of multimedia learning stressed the advantages of visual scaffolding for comprehension and retention, Oxford addressed the influence of cognitive preferences on language acquisition strategies [32,36,37]. Meanwhile, few studies have examined these dynamics in environments where ESP is enhanced by AI [4,6]. Although recent research on adaptive learning systems supports the idea that cognitive alignment enhances performance, their models are still only capable of superficial customization [38]. By combining performance measures with emotional reactions, this study offers a more comprehensive, multifaceted perspective, demonstrating how cognitive style influences not only students' feelings but also their learning outcomes. Furthermore, the qualitative findings cast doubt on the notion that AI systems are always successful, suggesting that they could replicate current educational disparities if not purposefully designed to accommodate cognitive diversity. By doing this, the study provides a more comprehensive foundation for further research by bridging the gaps between cognitive psychology, AI pedagogy, and ESP training.

According to recent research, reflective and kinesthetic learners often experience disengagement or emotional strain, underscoring the need for differentiated pedagogical strategies. In contrast, visual learners flourish in AI-enhanced ESP environments, as diagrammatic feedback closely aligns with their cognitive preferences. For example, to prevent favouring one modality over another and to promote inclusive, collaborative learning environments, AI-driven ESP classrooms must incorporate multiple intelligences [6]. Similarly, innovative AI-enhanced ESP environments can empower students by providing individualized feedback and variable pacing, directly satisfying reflective learners' need for more in-depth interaction [39]. These findings are supported by AI chatbots built using activity theory, which can help non-visual learners overcome fear and low self-efficacy by supporting a variety of cognitive-emotional regulation techniques [40]. When considered collectively, these studies suggest that a more complex categorization—beyond the conventional visual, reflective, and kinesthetic triad—may reveal more nuanced aspects of learner affect and cognition, enabling AI-supported ESP systems to provide adaptive interventions that boost self-esteem, reduce emotional obstacles, and ultimately improve language-learning outcomes.

In addition, deep learning systems are becoming more sophisticated by adjusting to a wide range of learner profiles. Instead of relying on static questionnaires, instructional tactics can be dynamically aligned using AI-based learning-style detection, which automatically recognizes cognitive preferences [5]. Sentiment analysis-based hybrid techniques improve feedback and pacing, especially for reflective learners who need intentional engagement [41]. In a similar vein, kinesthetic learners are supported with cognitive neuropsychology-informed adaptive evaluations that make sure physical contact and metacognitive reflection are not neglected [17]. When taken as a whole, these developments incorporate multimodal feedback, variable pacing, and embodied simulations, improving performance while removing emotional obstacles and redefining AI pedagogy around cognitive diversity, empathy, and customisation.

The study acknowledges several shortcomings despite its contributions. The fact that only one institution provided the sample may limit the applicability of the findings in different disciplinary or cultural contexts. Despite verification, the CLSI and EPEM tools might not fully capture the complexities of affective and cognitive involvement, especially in neurodiverse or multilingual groups. Furthermore, the study's AI system was not built with cognitive plasticity in mind, which restricted the range of experimental variance [14,26]. Future studies should investigate more designs, cross-institutional samples, and more dynamic AI systems with real-time cognitive profiling capabilities. Practically speaking, the results suggest that cognitive inclusivity, encompassing multimodal feedback, pacing flexibility, and bodily engagement in system architecture, should be given top priority by instructional designers and AI developers. The study recommends diversified instructional approaches for ESP teachers that respect learners' cognitive identities and promote not only language proficiency but also emotional fortitude and self-efficacy in AI-mediated contexts. Instead of employing categorical groups, future research could operationalise cognitive learning styles along continuous dimensions by capturing overlapping cognitive inclinations using mixture modelling or latent profile analysis. Alternatively, greater explanatory power could be achieved through multi-layered frameworks that integrate cognitive, metacognitive, and affective characteristics, such as strategy use, self-regulation, and emotional responses. Such models could be dynamically updated using learning analytics in AI-mediated learning environments, enabling cognitive profiles to change rather than stay constant in response to learner activity.

It is important to recognise the various methodological limitations of this study. First, the causal interpretation of the association between cognitive learning styles and ESP performance is limited by the mixed-methods design's reliance on correlational analyses. Second, the results cannot be generalised to other educational or technical contexts because the sample was drawn from a single university using a single AI-supported ESP platform. Third, self-reported inventories were used to quantify cognitive learning styles, which may oversimplify dynamic and overlapping cognitive profiles. Fourth, subjectivity and system-related bias may be introduced by combining teacher evaluations with AI-generated data in ESP performance metrics. Lastly, the qualitative data do not represent dynamic, real-time cognitive or affective changes because they are restricted to a particular system and a brief period of time. These constraints suggest that future research must be experimental, longitudinal, and multi-contextual.

6. Conclusions

By empirically demonstrating how different cognitive styles—visual, reflective, and kinesthetic—influence learner engagement and performance in deep learning-based educational systems, this study makes a significant contribution to the intersection of cognitive learning theory, AI-enhanced pedagogy, and ESP instruction. The study, which used a mixed-methods approach, found that visual learners routinely outperformed other learners on the ESP Performance Evaluation Matrix (EPEM). This finding was corroborated by both quantitative metrics and qualitative feedback, which showed a strong affinity for the system's graphical user interface. While kinesthetic learners reported disengagement due to the lack of embodied contact, reflective learners, despite their cognitive abilities, felt emotional distress with automated pacing and impersonal feedback. NVivo analysis also revealed emotional reactions as cross-cutting themes among non-visual learners, namely worry and decreased self-efficacy. These results underscore the need for instructional systems that are both pedagogically inclusive and technologically advanced, as cognitive congruence is a crucial factor in determining academic achievement and affective engagement in AI-mediated ESP contexts.

Beyond ESP education, the study's broader implications offer guidance for developing AI systems that cater to a range of cognitive and emotional learner characteristics. The results show that systems designed for visual processing may unintentionally exclude students with introspective or kinesthetic inclinations, challenging the widely held belief that AI-enhanced platforms are always beneficial. To promote fair learning experiences, a paradigm shift is necessary in the design of educational technology, prioritising multimodal feedback, flexible pacing, and bodily interaction. The study does have several drawbacks, though. The results may not be as generalizable across disciplinary and cultural contexts because the sample was taken from a single institution. Even though the tools have been validated, they might not adequately capture the complexity of learners' emotions and cognition, especially in neurodiverse or multilingual populations.

Furthermore, the investigation of dynamic learner-system interactions was limited by the AI system's lack of adaptive capabilities. Future studies should incorporate real-time cognitive profiling, investigate the effects of emotionally intelligent feedback mechanisms, and conduct further studies in various educational contexts. Our understanding of how AI can be successfully and ethically integrated into language instruction will grow as a result of these initiatives.

In summary, by highlighting how cognitive style influences the learner experience in AI-supported ESP contexts, our work contributes to the discussion on individualised learning. Instead of crushing human cognition and emotion into computational uniformity, it advocates redesigning educational technology to respect their uniqueness. By integrating cognitive psychology, AI pedagogy, and ESP education, the study lays the groundwork for learning systems that are more humane, sensitive, and inclusive. The need to design with empathy, teach with flexibility, and innovate with integrity is evident as more institutions incorporate AI into language instruction. Only then can we make sure that technology facilitates meaningful, egalitarian, and transformative learning rather than acting as a barrier. Future research should focus on several important areas to extend the reach of this study's recommendations. To ensure the findings are generalizable, researchers should first replicate the study across institutions, disciplines, and cultural contexts. Second, researchers should develop and evaluate cognitively adaptive AI-ESP systems with an emphasis on how learners with different cognitive styles are affected by modality, tempo, feedback, and embodied involvement. Third, dynamic research is needed to examine how learner engagement and cognitive preferences change over time in adaptive AI environments. Fourth, rather than focusing solely on language proficiency, future studies should expand the scope of outcome evaluations to include affective, metacognitive, and professional competencies. Finally, through interdisciplinary collaboration among linguistics, psychology, and AI development, research should emphasize equitable and ethical AI design, especially for neurodiverse and multilingual learners.

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Informed Consent Statement

Informed consent was obtained from all subjects involved in the study.

Data Availability Statement

All data are available in the article.

Conflicts of Interest

The authors declare no conflict of interest.

AI Use Statement

Copilot 365 was only used by the writers to verify grammar, improve sentence structure, and make the English text in this paper easier to read. All ideas, data, analysis, and conclusions given herein are entirely the responsibility of the writers. The writers carefully examined and oversaw the application of AI.

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