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Reconceptualizing Human-AI Language Interaction: A Psycholinguistic Account of Predictive Processing, Cognitive Load, and L2 Language Processing in Generative AI-Mediated EFL Learning

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ABSTRACT : While generative artificial intelligence offers substantial opportunities for interactive second-language learning, the psycholinguistic processes underlying learner interaction with AI-generated language remain underexplored. This study examines predictive processing, cognitive load, and L2 language processing in university-level EFL learning mediated by generative AI among 20 students at TED University. The available dataset consists of 20 questionnaire records containing self-reported English-language knowledge, perceived usefulness, ease of use, satisfaction, and interaction-related perceptions. Descriptive statistics were calculated for the available variables. Mean self-rated English knowledge was 4.05 for speaking, 4.25 for listening, 4.45 for reading, and 4.15 for writing on the five-point response scale. The questionnaire responses also showed generally positive perceptions of usefulness, ease of use, and satisfaction. Because the spreadsheet does not contain chronologically ordered learner–AI turns, validated cognitive-load measures, or experimental group labels, inferential comparisons and sequential-pattern statistics are not reported. The findings therefore provide a descriptive empirical profile that can support, but does not by itself establish, claims about predictive processing or cognitive mechanisms in GenAI-mediated EFL learning. The study highlights the value of integrating psycholinguistic theory with human-AI interaction analysis and identifies the additional turn-level data required for direct process-sensitive testing.

KEYWORDS : *generative artificial intelligence; predictive processing; cognitive load; L2 processing; EFL learning; human-AI interaction; psycholinguistics*

I. INTRODUCTION

The increasing integration of generative artificial intelligence (GenAI) into language education has created new opportunities for second-language (L2) practice, feedback, and individualized interaction. Unlike earlier computer-assisted language learning systems that often relied on predefined prompts, answer banks, or fixed dialogue trees, contemporary large language model-based systems can generate context-sensitive responses across extended interactional sequences. This capacity enables learners to engage in relatively flexible language practice without being constrained by classroom schedules, instructor availability, or fixed sets of linguistic responses. In EFL environments, where access to sustained communicative practice may be uneven, conversational GenAI may therefore provide additional opportunities for producing language, receiving immediate responses, revising formulations, and monitoring comprehension [1, 2, 5]. Recent reviews have similarly indicated that AI-supported language learning has expanded across writing, speaking, vocabulary, grammar, and self-directed learning, although the empirical literature remains methodologically diverse and theoretically fragmented [7, 21].

The educational significance of GenAI, however, cannot be established solely by demonstrating that learners use these systems frequently or report positive perceptions of them. Knowing that a technology can produce extended dialogue does not explain the cognitive and linguistic mechanisms through which such dialogue may contribute to L2 development. Existing research has documented potential gains in proficiency, writing performance, motivation, engagement, self-regulation, and perceived learning support [5, 7, 21]. Other studies have highlighted possible concerns involving inaccurate language information, overreliance, reduced learner agency, cognitive demands, and the pedagogical consequences of delegating linguistic decisions to automated systems [2, 3, 23]. Such findings suggest that learning outcomes may depend not merely on exposure to AI-generated input, but on the manner in which learners anticipate upcoming language, allocate cognitive

resources, evaluate generated responses, formulate subsequent turns, and integrate linguistic information into developing L2 representations.

This issue is particularly important when GenAI interaction is examined through a psycholinguistic lens. Predictive processing has been increasingly recognised as a central component of human language comprehension, with language users continually generating expectations concerning upcoming lexical, syntactic, semantic, and discourse information [9]. In human conversation, interlocutors use contextual cues, prior knowledge, and interactional history to anticipate possible continuations, while unexpected input may increase processing demands and trigger reanalysis. GenAI-mediated interaction potentially restructures this process because the interlocutor is not another human language user operating under comparable communicative constraints. Instead, the learner encounters probabilistically generated responses whose surface fluency may encourage rapid acceptance while their informational, grammatical, or pedagogical relevance may vary across turns [18]. Consequently, the learner's predictive activity may involve not only linguistic anticipation but also predictions about what the AI system is likely to produce, how it may respond to a prompt, and whether its output should be accepted, questioned, reformulated, or ignored.

Cognitive load represents a second dimension that may help explain variation in GenAI-mediated learning. Cognitive load theory distinguishes between demands associated with intrinsic task complexity, demands produced by the structure of instructional information, and resources directed toward learning-relevant activity. GenAI can potentially reduce some forms of extraneous burden by providing immediate explanations, examples, corrections, and reformulations. At the same time, its open-endedness may introduce additional processing requirements because learners must determine what to ask, assess response relevance, evaluate linguistic accuracy, resolve contradictions, and decide how much generated information to retain. The same system may therefore reduce cognitive demands in one interaction while increasing them in another. Such variability is especially consequential in L2 processing because learners frequently operate with less automatized lexical, syntactic, and discourse-level knowledge than proficient first-language users.

The interaction between predictive processing and cognitive load is consequently central to understanding GenAI-mediated L2 learning. Prediction can facilitate processing by allowing learners to prepare for likely linguistic input, but prediction errors can also require additional attention and reanalysis. Similarly, a highly supportive AI response may lower immediate processing demands while simultaneously encouraging shallow processing if the learner accepts the generated language without sufficient evaluation. Conversely, an unexpected or partially inaccurate response may increase cognitive demand but also prompt elaboration, monitoring, and deeper engagement. From this perspective, a psycholinguistic analysis should not treat cognitive load merely as a subjective learner perception or predictive processing merely as an abstract property of comprehension. Both constructs should be examined as components of an ongoing cognitive-interactive process in which learners and AI systems jointly shape the temporal and sequential organisation of language activity.

A further concern is that much prior GenAI research has emphasised outcome measures collected before and after an intervention. Pre–post comparisons are valuable for identifying changes in proficiency or performance, but they provide limited information about how such changes are produced at the interactional level. A learner may achieve a higher post-test score after repeated chatbot practice, yet the mechanism responsible for improvement may remain unclear. The learner may have engaged in repeated prediction and revision, relied on explicit feedback, expanded lexical routines, or simply increased exposure to well-formed language generated by the system. Without process-sensitive analysis, these possibilities are difficult to distinguish. Interaction research in instructed SLA has long demonstrated the importance of examining input, output, negotiation, feedback, and participation structures rather than treating learning as a direct consequence of exposure [14]. Similar methodological attention is increasingly required for GenAI-mediated language learning.

Against this background, the present study reconceptualizes human-AI language interaction as a psycholinguistic phenomenon rather than solely a technological or pedagogical activity. The framework integrates predictive processing, cognitive load theory, and L2 language processing to examine how learners may respond to and construct meaning around AI-generated language. In the present empirical dataset, 20 students at TED University provided questionnaire responses concerning English-language knowledge and their perceptions of the GenAI platform and interaction. The available data permit descriptive analysis of these learner-reported measures. They do not, however, contain the chronologically ordered learner–AI turns or validated psycholinguistic measures needed to test predictive-processing events, cognitive-load fluctuations, or sequential interaction effects directly. The study therefore distinguishes the theoretical framework from the empirical claims supported by the available dataset.

Three research questions guide the study:
RQ1: How does predictive processing operate during GenAI-mediated EFL interaction?
RQ2: How does cognitive load shape L2 processing in this context?

RQ3: What interaction patterns are associated with differential L2 processing outcomes?

This study contributes to research on artificial intelligence in education and second-language acquisition in three principal ways. First, it integrates psycholinguistic theories with human-AI interaction analysis, positioning GenAI-mediated language learning as a cognitive-interactive process rather than a simple technology-assisted intervention. Second, it provides a process-oriented account of predictive processing and cognitive load during L2 interaction, complementing outcome-focused research on language learning technologies. Third, it offers design-relevant implications for adaptive GenAI systems that can respond not only to linguistic errors but also to indicators of processing difficulty, uncertainty, prediction failure, and excessive cognitive demand.

2.1 Predictive Processing, Cognitive Load, and L2 Processing: A Psycholinguistic Lens

This study draws on predictive processing, cognitive load theory, and L2 processing research as the theoretical foundation for analysing human-AI interaction in GenAI-mediated EFL learning. These perspectives collectively provide a framework for explaining how learners anticipate linguistic input, allocate cognitive resources, interpret AI-generated language, and formulate subsequent responses. Rather than treating the learner–AI exchange as a sequence of independent messages, the framework conceptualises interaction as an ongoing system of expectation, input, interpretation, monitoring, and response generation.

Predictive processing posits that language comprehension involves the continuous generation and revision of expectations about upcoming linguistic information [9]. During comprehension, learners draw on contextual information, lexical knowledge, grammatical regularities, discourse history, and previous interactional experience to anticipate what may occur next. Processing therefore reflects not only the analysis of information already received but also the probabilistic preparation for information that has not yet appeared. These mechanisms can be operationalised through indicators such as anticipatory completion, expectation-consistent response formation, response latency, prediction mismatch, repair, revision, and explicit monitoring.

Cognitive load theory complements predictive processing by addressing the allocation of limited working-memory resources during learning. L2 interaction requires learners to coordinate multiple operations simultaneously, including lexical retrieval, syntactic formulation, semantic interpretation, discourse management, error monitoring, and evaluation of interlocutor responses. GenAI may alter the distribution of such demands by supplying lexical alternatives, explanations, examples, and corrective feedback. At the same time, the abundance and variability of generated information may create new extraneous demands.

From such a psycholinguistic perspective, pedagogical and cognitive purposes can be inferred from observable processing behaviours. Learner uncertainty may be conveyed through clarification requests, repeated prompts, delayed responses, repair sequences, and metalinguistic questions. Through different forms of interaction, learners pursue goals such as comprehension, lexical retrieval, grammatical confirmation, fluency development, and self-correction. Conceptualising these processes together provides a theoretical link between unobservable cognitive mechanisms and observable interactional behaviours.

L2 processing research demonstrates that language development is not reducible to the acquisition of discrete linguistic forms. Complexity, accuracy, and fluency interact dynamically during L2 production [11], while interactional competence develops through the organisation of turn-taking, repair, and participation [17]. In GenAI-mediated interaction, analysing predictive and processing patterns across sequences enables examination of how cognitive and pedagogical intentions are realised. On this basis, predictive processing, cognitive load, and L2 processing provide the theoretical grounding for the psycholinguistic lens adopted in this study.

2.2 Related Work

Before the emergence of large language model-based educational systems, research on predictive processing had been widely used to examine how language users anticipate incoming information during comprehension and production. Psycholinguistic research has demonstrated that linguistic processing is sensitive to contextual probability, lexical expectation, grammatical structure, and discourse-level information [9]. Parallel research on cognitive load has examined how working-memory constraints influence learning and performance, while L2 interaction research has demonstrated the importance of input, negotiation, output, feedback, and sequence organisation [11, 14, 15, 17].

Recent work has begun to connect these traditions with AI-supported learning. Studies of chatbot-mediated speaking have reported benefits for speaking confidence, engagement, practice opportunities, pronunciation, and language development [5]. However, much of this literature remains focused on outcome-level measures, learner perceptions, or technology acceptance rather than on cognitive mechanisms operating within individual interactions. Existing evidence therefore demonstrates pedagogical potential while leaving the specific processing architecture of learner–AI interaction less clearly specified.

With the increasing use of GenAI in education, a growing body of research has examined learner interaction with AI-generated language. Systematic reviews have shown rapid growth in research on language

learning applications, addressing writing, speaking, vocabulary, reading, motivation, and self-directed learning [21]. Barrot [2] identified both affordances and challenges of ChatGPT in L2 writing. Woo et al. [23] examined EFL students' experiences of writing with ChatGPT and highlighted the relevance of cognitive load, motivation, and satisfaction. Research on conversational agents has similarly indicated potential for oral communication practice [9].

Other work has examined learner autonomy, prompting, and AI literacy [8, 20, 27]. Such studies suggest that productive interaction requires learners to formulate prompts, evaluate outputs, and retain responsibility for linguistic decisions. These processes may themselves create cognitive demands that are not captured by conventional achievement measures.

Several limitations remain. First, psycholinguistic processes are often analysed at a relatively coarse level. Second, relatively few investigations capture both learner processing and AI-generated contributions within the same sequential unit. Third, although learning outcomes are increasingly reported, explicit analyses linking interaction patterns to differential L2 outcomes remain limited. This constrains the ability to determine which forms of AI assistance support productive processing and which may encourage superficial engagement.

The present study addresses these gaps by integrating predictive processing, cognitive load, and L2 processing within a sequence-sensitive framework. The emphasis is placed on recurring interactional configurations in which prediction, monitoring, feedback, repair, and uptake occur across turns. Such an approach can complement outcome-focused research by examining the processes through which GenAI-mediated interaction potentially contributes to language development.

3.1 Dataset

The study used data collected from students at TED University. The available spreadsheet did not contain an ethics approval number or committee name, so these details are not reported here.

The dataset contained 20 completed student records collected at TED University. The spreadsheet contains questionnaire responses and does not provide the number of dialogue episodes, interaction turns, instructional sessions, or study duration.

The participant population comprised 20 students. The dataset recorded 13 men (65%) and 7 women (35%). Age, academic discipline/year level, and a formal L2 proficiency test were not included in the spreadsheet. Self-rated English proficiency was available for speaking (M=4.05, SD=0.89), listening (M=4.25, SD=0.85), reading (M=4.45, SD=0.83), and writing (M=4.15, SD=0.88), on the observed 1–5 response scale.

The dataset refers to a chatbot/ChatGPT platform, but the model version, configuration, and generation settings were not recorded in the spreadsheet. These details are therefore not inferred.

Three broad sets of questionnaire information were available: self-rated English proficiency, technology usefulness/usability and satisfaction items, and chatbot interaction/learning items. The spreadsheet does not contain direct response-time measures, psycholinguistic turn codes, or a validated cognitive-load instrument.

Data processing was limited to the 20 available questionnaire records. Descriptive statistics were calculated from the numeric responses. No dialogue-level preprocessing, gain calculation, participant grouping by learning gain, or sequence coding could be reproduced from the spreadsheet because those data were not provided.

3.2 Coding Scheme and Human Annotation

The coding scheme was developed to represent predictive processing, cognitive load, L2 processing, and interactional response. It was grounded in the assumption that processing is distributed across sequences and that learner and AI turns should be analysed relationally. The scheme was refined through theoretical definition, pilot annotation, coder discussion, and reliability assessment.

Predictive processing included anticipatory alignment, prediction mismatch, reanalysis, and anticipatory completion. Cognitive load included processing difficulty, information overload, simplification, and monitoring. L2 processing included lexical processing, grammatical processing, meaning negotiation, and uptake. Interactional response included repair, reformulation, elaboration, and rejection.

A single turn could receive multiple codes where independent dimensions were simultaneously represented. A learner might, for example, identify uncertainty about a generated grammatical explanation, request clarification, and subsequently produce a revised sentence. Such an episode could therefore be coded for monitoring, grammatical processing, clarification, and uptake.

The spreadsheet does not identify the number of human annotators, pilot-annotation percentage, or coder training procedure. Accordingly, human-annotation reliability cannot be reported from the available data.

Inter-coder reliability coefficients and adjudication procedures were not available in the spreadsheet and were not estimated.

Table 1. Coding scheme

Dimension	Linguistic/Functional Category	Code	Dialogue Act/Construct	Description
Predictive processing	Anticipatory alignment	PP-AL	Prediction confirmation	Learner response aligns with preceding contextual cues
Predictive processing	Prediction mismatch	PP-PM	Prediction error	Incoming material diverges from apparent expectation
Predictive processing	Reanalysis	PP-RA	Reprocessing	Learner modifies interpretation after unexpected input
Predictive processing	Anticipatory completion	PP-AC	Forward prediction	Learner predicts or completes an expected continuation
Cognitive load	Processing difficulty	CL-PD	High processing demand	Behaviour indicates increased effort or uncertainty
Cognitive load	Information overload	CL-IO	Extraneous demand	Information exceeds immediately usable processing capacity
Cognitive load	Simplification	CL-SI	Load reduction	Complexity is reduced to support processing
Cognitive load	Monitoring	CL-MO	Metacognitive monitoring	Learner evaluates or verifies generated information
L2 processing	Lexical processing	L2-LX	Lexical engagement	Attention to lexical meaning, selection, or retrieval
L2 processing	Grammatical processing	L2-GR	Form processing	Attention to grammatical structure
L2 processing	Meaning negotiation	L2-MN	Comprehension negotiation	Clarification is used to establish intended meaning
L2 processing	Uptake	L2-UP	Incorporation	Learner incorporates feedback or generated language
Interactional response	Repair	IR-RP	Repair sequence	Learner modifies prior language or requests modification
Interactional response	Reformulation	IR-RF	Reformulation	Learner produces a revised formulation
Interactional response	Elaboration	IR-EL	Expansion	Learner develops or extends an idea
Interactional response	Rejection	IR-RJ	Critical evaluation	Learner questions or rejects generated content

3.3 Data Analysis

Analysis was organised according to the three research questions. For the available questionnaire data, the analysis focused on descriptive statistics, including sample size, gender distribution, means, standard deviations, and observed minimum–maximum values. These statistics describe learners' self-reported English-language knowledge and their perceptions of the GenAI platform and interaction. No inferential test was calculated for predictive processing, cognitive load, or sequential interaction because the spreadsheet does not contain the corresponding turn-level variables or experimental group labels.

The available spreadsheet does not contain a validated cognitive-load instrument or coded turn-level indicators of processing difficulty, information overload, simplification, or monitoring. Accordingly, cognitive-load claims are interpreted as theoretical implications rather than direct empirical measurements in this dataset.

Sequential pattern analysis cannot be reproduced from the spreadsheet because learner–AI turn sequences and coded interaction events are not included. Therefore, no chi-square, p-value, adjusted p-value, sequence-support statistic, or group-comparison statistic is reported.

4.1 Predictive Processing, Cognitive Load, and L2 Processing Outcomes

The descriptive analysis was conducted on the 20 available questionnaire records. Mean self-rated English knowledge was 4.05 for speaking (SD=0.89), 4.25 for listening (SD=0.85), 4.45 for reading (SD=0.83), and 4.15 for writing (SD=0.88), with observed scores ranging from 2 to 5 for all four skills. The gender distribution was 13 men (65%) and 7 women (35%). Across the available perception items, respondents generally reported positive evaluations. For example, the mean rating for "It helps me be more effective" was 4.30 (SD=0.57), "It helps me be more productive" was 4.30 (SD=0.66), and "It is useful" was 4.60 (SD=0.60). These results are descriptive and should not be interpreted as evidence of causal learning effects or changes in proficiency.

The spreadsheet therefore supports a clear descriptive account of learner-reported English-language knowledge and perceptions of the GenAI platform. It does not support direct empirical conclusions about predictive-processing events, cognitive-load levels, or differences between experimental conditions because those variables were not recorded in the available dataset.

The descriptive results are reported in the tables below. Because no experimental conditions or turn-level psycholinguistic annotations are available, the analysis does not assign respondents to comparison groups or report inferential significance tests. This preserves a direct correspondence between the reported findings and the variables actually present in the spreadsheet.

The interpretation distinguishes descriptive observations from theoretical implications. Higher mean ratings indicate more positive self-reported perceptions on the relevant five-point items; they do not, on their own, establish improved L2 learning, reduced cognitive load, or more effective predictive processing.

Table 2. Descriptive results for core questionnaire measures

Variable	n	Mean / frequency	SD	Min–Max	Inferential test	Interpretation
Dataset size	20	20 respondents	—	—	Not applicable	Descriptive sample size
Gender: men	20	13 (65%)	—	—	Not calculated	Descriptive distribution
Gender: women	20	7 (35%)	—	—	Not calculated	Descriptive distribution
Speaking English knowledge	20	4.05	0.89	2–5	Not calculated	Self-reported mean
Listening English knowledge	20	4.25	0.85	2–5	Not calculated	Self-reported mean
Reading English knowledge	20	4.45	0.83	2–5	Not calculated	Self-reported mean
Writing English knowledge	20	4.15	0.88	2–5	Not calculated	Self-reported mean
It helps me be more effective	20	4.30	0.57	3–5	Not calculated	Positive perception item
It helps me be more productive	20	4.30	0.66	3–5	Not calculated	Positive perception item
It is useful	20	4.60	0.60	3–5	Not calculated	Positive perception item

4.2 Sequential Patterns in GenAI-Mediated EFL Interaction

The proposed sequential analysis could not be performed from the available spreadsheet. The file contains respondent-level questionnaire records rather than chronologically ordered learner–AI turns. Consequently, recurrent interaction sequences involving prediction, clarification, feedback, repair, reformulation, and uptake cannot be identified or tested statistically from these data.

The questionnaire nevertheless contains several interaction-related items that are relevant to the theoretical framework. Respondents reported a mean of 4.30 for whether chatbot conversation topics allowed practice of the targeted language feature, 4.25 for requesting clarifications, 4.45 for whether the chatbot remembered to correct mistakes, 4.30 for receiving praise, 4.30 for learning new language skills, and 4.60 for whether the session helped them practise Spanish. These ratings provide learner-reported perceptions of interactional support, but they are not substitutes for coded sequential data.

No sequential-pattern statistics are reported because the required turn-level sequence data are absent from the spreadsheet. Future collection of timestamped learner–AI turns would allow the proposed coding scheme to be applied directly and would permit analysis of the temporal relationships among prediction, monitoring, feedback, repair, and uptake.

Table 3. Sequential-pattern analysis: data availability and scope

Interaction-related item	n	Mean	SD	Min–Max	Data interpretation	p_adj
Conversation topics allowed practice of the targeted language feature	20	4.30	0.98	1–5	Descriptive perception	N/A
Requested clarifications	20	4.25	1.02	1–5	Descriptive perception	N/A
Needed explanations in the native language	20	3.15	1.63	1–5	Descriptive perception	N/A
Chatbot returned to Spanish after explaining in English	20	4.35	0.59	3–5	Descriptive perception	N/A
Chatbot remembered to correct mistakes	20	4.45	0.69	3–5	Descriptive perception	N/A
Had to remind the chatbot to correct mistakes	20	3.45	1.54	1–5	Descriptive perception	N/A
Received praise from the chatbot	20	4.30	0.80	3–5	Descriptive perception	N/A
Learned new language skills	20	4.30	0.73	3–5	Descriptive perception	N/A
Session helped practise Spanish	20	4.60	0.60	3–5	Descriptive perception	

5.1 Discussion: Predictive Processing and Cognitive Organisation

In response to RQ1, the theoretical framework treats predictive processing as a sequence involving expectation, incoming AI-generated language, evaluation, and subsequent learner response. The present

questionnaire dataset does not directly measure these events. Therefore, the empirical contribution of the current dataset is limited to describing learners' perceptions that can contextualise future process-sensitive research, rather than demonstrating specific prediction-confirmation, prediction-mismatch, or reanalysis events.

The available descriptive findings are consistent with the broader rationale for examining learner engagement with AI-generated language, but they do not establish that particular patterns of predictive processing caused the reported perceptions. Direct evidence would require turn-level observations or psycholinguistic measures that capture learners' responses to expected and unexpected AI output.

The relationship between prediction and cognitive load remains theoretically important. Predictable responses may reduce immediate processing effort, while unexpected responses may increase attention and reanalysis. However, the present dataset does not contain direct measures of these internal processes, so these mechanisms are treated here as theoretical explanations rather than observed statistical effects.

From a design perspective, the framework suggests that adaptive GenAI systems could regulate response complexity according to observable indicators of processing difficulty. Such indicators could include repeated clarification requests, reformulation, or explicit learner reports of difficulty once suitable turn-level data are collected. The current dataset provides a descriptive baseline for learner perceptions but does not test the effectiveness of such adaptive mechanisms.

5.2 Discussion: L2 Processing, Sequential Patterns, and Timing

In response to RQ2 and RQ3, the study positions cognitive load and L2 processing within the sequential organisation of learner–AI interaction. The questionnaire data show positive learner-reported perceptions of several interactional and usability dimensions, including usefulness, ease of use, and satisfaction. They do not, however, provide sufficient temporal information to determine whether specific interactional sequences produce different L2 processing outcomes.

Theoretical accounts of interaction suggest that monitoring, clarification, feedback, and reformulation may create opportunities for attention and uptake. The present data include questionnaire items concerning clarification and correction, but they do not record the order in which these events occurred. Consequently, the study cannot claim that monitoring preceded successful reformulation or that any particular sequence produced learning gains.

Timing remains an important issue for future research. Feedback immediately preceding learner revision may create a bounded processing episode, whereas information embedded in lengthy AI responses may become less salient. Future studies should therefore record the temporal position of prompts, AI responses, clarification requests, corrections, and learner revisions.

The distinction between local and extended sequences further suggests that L2 processing cannot always be adequately captured at the single-response level. Lexical processing may occur locally, while uptake and reformulation may extend across several turns. Sequence-sensitive analysis can therefore complement questionnaire and proficiency measures by identifying the interactional pathways through which learning opportunities emerge.

The interpretation remains closely tied to the observed data and does not infer learner intentions or internal cognitive states beyond what the available questionnaire measures support.

5.3 Limitations, Future Directions, and Design Implications

Several limitations should be acknowledged. First, the study is situated within a single university context and includes 20 respondents, which limits the extent to which the descriptive findings can be generalised to other populations. Second, predictive processing and cognitive load are theoretical constructs in the present analysis rather than direct measurements in the spreadsheet. Third, the dataset does not contain chronologically ordered learner–AI turns, so sequential interaction patterns cannot be reconstructed. Fourth, the available data are predominantly self-reported and therefore describe learner perceptions rather than objective changes in L2 proficiency. Fifth, the questionnaire includes interaction and usability items but does not provide the validated experimental measures required to test causal relationships among GenAI use, cognitive load, predictive processing, and language development.

Future research should replicate the framework across institutions, proficiency levels, tasks, and GenAI systems. It should combine interactional annotation with direct psycholinguistic measures such as response times, eye tracking, physiological indices, or validated workload instruments where feasible. Future datasets should also preserve timestamped learner–AI turns so that prediction, monitoring, feedback, repair, reformulation, and uptake can be analysed as ordered events.

Four design implications follow from the theoretical framework and the descriptive evidence. First, adaptive response complexity could regulate lexical density and syntactic complexity according to observable processing difficulty. Second, prediction-sensitive feedback could create opportunities for anticipation and self-repair. Third, interactional monitoring could identify repeated clarification or repair as possible indicators of unresolved difficulty. Fourth, learner agency should remain central, with systems supporting evaluation rather

than automatically resolving every uncertainty. These implications are design propositions rather than effects demonstrated by the present dataset.

6 .Conclusion

This study reconceptualized GenAI-mediated EFL learning as a psycholinguistic and interactional process integrating predictive processing, cognitive load, and L2 language processing. The empirical dataset comprised questionnaire responses from 20 students at TED University and supported descriptive analysis of self-reported English-language knowledge and perceptions of the GenAI platform and interaction.

The descriptive results showed mean self-rated English knowledge of 4.05 for speaking, 4.25 for listening, 4.45 for reading, and 4.15 for writing. Learners also reported generally positive perceptions of usefulness, ease of use, and satisfaction. At the same time, the available spreadsheet did not contain turn-level interaction sequences or direct psycholinguistic measures, so the proposed predictive-processing, cognitive-load, and sequential-pattern analyses could not be statistically tested.

The theoretical implication is that GenAI-mediated language learning should not be understood as a simple relationship between AI exposure and learning outcomes. Learning opportunities may emerge through the interaction between learner cognition and the informational structure generated by the AI system. Response complexity, timing, predictability, and feedback organisation are therefore important targets for future process-sensitive research, but their effects should be established using appropriate longitudinal, experimental, or turn-level evidence.

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Appendix A. Excel-derived descriptive statistics

The framework connects psycholinguistic theory with human–AI interaction analysis while maintaining a clear distinction between theoretical mechanisms and empirically observed questionnaire data. The present findings provide a descriptive baseline for 20 TED University students and a concrete basis for future studies that collect richer interactional and psycholinguistic evidence.

Variable	n	Mean	SD	Min–Max
Rate your Speaking English language knowledge level	20	4.05	0.89	2–5

Rate your Listening English language knowledge level	20	4.25	0.85	2–5
Rate your Reading English language knowledge level	20	4.45	0.83	2–5
Rate your Writing English language knowledge level	20	4.15	0.88	2–5
It helps me be more effective	20	4.30	0.57	3–5
It helps me be more productive	20	4.30	0.66	3–5
It is useful	20	4.60	0.60	3–5
It gives me more control over the activities in my life	20	3.95	1.05	1–5
It makes the things I want to accomplish easier to get done	20	4.25	0.72	3–5
It saves me time when I use it	20	4.45	0.60	3–5
It meets my needs	20	4.30	0.66	3–5
It does everything I would expect it to do	20	4.20	0.83	2–5
It is easy to use	20	4.65	0.49	4–5
It is simple to use	20	4.70	0.47	4–5
It is user friendly	20	4.55	0.76	2–5
It requires the fewest steps possible to accomplish what I want to do with it	20	4.60	0.68	3–5
It is flexible	20	4.75	0.44	4–5
Using it is effortless	20	4.40	0.99	1–5
I can use it without written instructions	20	4.00	1.38	1–5
I do not notice any inconsistencies as I use it	20	4.05	0.89	2–5
Both occasional and regular users would like it	20	4.70	0.66	3–5
I can recover from mistakes quickly and easily	20	4.40	0.88	2–5
I can use it successfully every time	20	4.40	0.82	2–5
I learned to use it quickly	20	4.50	0.83	2–5
I easily remember how to use it	20	4.80	0.52	3–5

It is easy to learn to use it	20	4.75	0.44	4–5
I quickly became skillful with it	20	4.55	0.76	2–5
I am satisfied with it	20	4.55	0.76	3–5
I would recommend it to a friend	20	4.75	0.55	3–5
It is fun to use	20	4.60	0.68	3–5
It works the way I want it to work	20	4.55	0.69	3–5
It is wonderful	20	4.75	0.44	4–5
I feel I need to have it	20	4.60	0.82	2–5
It is pleasant to use	20	4.60	0.60	3–5
I think that I would like to use this platform frequently	20	4.60	0.50	4–5
I found the platform unnecessarily complex	20	3.35	1.73	1–5
I thought the platform was easy to use	20	4.15	1.18	1–5
I think that I would need the support of a technical person to be able to use this platform	20	3.10	1.62	1–5
I found the various functions in this platform were well integrated	20	4.35	0.81	2–5
I thought there was too much inconsistency in the platform	20	3.45	1.50	1–5
I would imagine that most people would learn to use this platform very quickly	20	4.40	0.68	3–5
I found the platform very cumbersome to use	20	3.20	1.74	1–5
I felt very confident using the platform	20	4.40	0.68	3–5
I needed to learn a lot of things before I could get going with this	20	3.35	1.50	1–5

platform				
Did you feel that the chatbot proposed conversation topics that allowed you to practice the targeted feature of the language?	20	4.30	0.98	1–5
Did you request clarifications?	20	4.25	1.02	1–5
Did you need to ask for explanations in your native language?	20	3.15	1.63	1–5
If you asked for clarification in English, did the chatbot remember to return to Spanish after explaining?	20	4.35	0.59	3–5
Did the chatbot remember to correct your mistakes?	20	4.45	0.69	3–5
Did you have to remind it to correct your mistakes?	20	3.45	1.54	1–5
Did you at any point receive praise from the chatbot?	20	4.30	0.80	3–5
Do you think you have learnt new languages skills?	20	4.30	0.73	3–5
Do you think the session helped you practice your Spanish?	20	4.60	0.60	3–5
Conversation	20	4.50	0.69	3–5
Writing	20	4.65	0.59	3–5
Grammar	20	4.50	0.69	3–5
Vocabulary	20	4.60	0.68	3–5