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COGNITIVE ANALYSIS OF LOGICAL-SEMANTIC STRUCTURES IN LLMS: ISSUES OF LINGUISTIC REDUCTION

Abstract

Future language teachers meet AI-enabled language learning tools twice: as learners who use them now, and as professionals who may soon bring them into their own classrooms. This article reports a cross-sectional survey of pre-service English teachers at one Kazakhstani pedagogical university. Thirty-eight third- and fourth-year students took part, and 33 confirmed using AI-enabled language learning tools within the previous twelve months. The questionnaire was adapted from the Technology Acceptance Model and covered perceived usefulness, perceived ease of use, behavioral intention, an additional block on future professional use, a usage profile, and two open-ended questions. Internal consistency of the multi-item scales was satisfactory (Cronbach's alpha 0.74–0.80). ChatGPT-type chatbots turned out to be the most widely used tools (81.8%), and vocabulary and writing were the skills students practised most often. Perceived usefulness received the highest composite rating ($M = 3.80$) and perceived ease of use the lowest ($M = 3.44$). Usefulness correlated positively with behavioral intention ($\rho = 0.53$, $p = 0.002$), whereas usage frequency showed no significant association with intention. Open-ended responses pointed to infrastructural barriers, distrust of answer accuracy, and the quality of Kazakh-language adaptation. Implications for foreign language teacher education programmes are discussed.

Keywords: *artificial intelligence; AI-enabled language learning tools; technology acceptance model; pre-service English teachers; foreign language education; ChatGPT; perceived usefulness; behavioral intention; AI literacy; Kazakhstan.*

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БОЛАШАҚ АҒЫЛШЫН ТІЛІ МҰҒАЛІМДЕРІНІҢ ЖИ ҚОЛДАЙТЫН ТІЛ ҮЙРЕНУ ҚҰРАЛДАРЫН ҚАБЫЛДАУЫ ЖӘНЕ ҚОЛДАНУЫ

Аңдатпа

Білім берудегі жасанды интеллект технологияларының қарқынды таралуы болашақ тіл мұғалімдерінің ЖИ қолдайтын тіл үйрену құралдарына қатысты ұстанымын зерттеудің өзектілігін арттырып отыр: олар бұл құралдарды білім алушы ретінде пайдаланып, болашақта кәсіби қызметінде қолдануы мүмкін. Мақалада бір қазақстандық педагогикалық ЖОО-ның болашақ ағылшын тілі мұғалімдері арасында жүргізілген кросс-секциялық сауалнамалық зерттеу нәтижелері баяндалады. Зерттеуге 3–4-курстың 38 студенті қатысты, олардың 33-і соңғы он екі айда ЖИ қолдайтын тіл үйрену құралдарын пайдаланғанын растады. Сауалнама технологияны қабылдау моделі негізінде бейімделді және пайдалы деп қабылдауды, пайдалану жеңілдігін, пайдалану ниетін, болашақ кәсіби қолдануды зерделейтін қосымша блокты, пайдалану профилін және екі ашық сұрақты қамтыды. Шкалалардың ішкі үйлесімділігі қанағаттанарлық (Cronbach's alpha 0,74–0,80). Ең жиі пайдаланылатын құрал — ChatGPT типті чат-боттар (81,8%); құралдар көбіне лексика мен жазылым дағдыларын дамыту үшін қолданылады. Пайдалы деп қабылдау ең жоғары ($M = 3,80$), пайдалану жеңілдігі ең төмен ($M = 3,44$) бағаланды. Пайдалылық пен пайдалану ниеті

арасында оң байланыс анықталды ($\rho = 0,53$; $p = 0,002$), ал пайдалану жиілігі мен ниет арасындағы байланыс мәнді болмады. Ашық жауаптарда инфрақұрылымдық кедергілер, жауап дәлдігіне сенімсіздік және қазақ тіліне бейімдеу сапасы аталды. Шетел тілі мұғалімдерін даярлау бағдарламаларына арналған ұсынымдар беріледі.

Түйін сөздер: жасанды интеллект; ЖИ қолдайтын тіл үйрену құралдары; технологияны қабылдау моделі; болашақ ағылшын тілі мұғалімдері; шеттілдік білім беру; ChatGPT; пайдалы деп қабылдау; пайдалану ниеті; ЖИ сауаттылығы; Қазақстан.

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ПРИНЯТИЕ И ИСПОЛЬЗОВАНИЕ ИИ-ИНСТРУМЕНТОВ ДЛЯ ИЗУЧЕНИЯ ЯЗЫКА БУДУЩИМИ УЧИТЕЛЯМИ АНГЛИЙСКОГО ЯЗЫКА

Аннотация

Быстрое распространение технологий искусственного интеллекта в образовании обуславливает необходимость изучения того, как будущие учителя языка воспринимают ИИ-инструменты для изучения языка: они используют их как обучающиеся и могут применять в профессиональной деятельности. В статье представлены результаты кросс-секционного опросного исследования будущих учителей английского языка одного казахстанского педагогического вуза. Участие приняли 38 студентов 3–4 курсов, из них 33 подтвердили использование ИИ-инструментов для изучения языка за последние двенадцать месяцев. Анкета адаптирована на основе модели принятия технологий и охватывала воспринимаемую полезность, простоту использования, намерение использования, дополнительный блок о профессиональном применении, профиль использования и два открытых вопроса. Внутренняя согласованность шкал была удовлетворительной (Cronbach's alpha 0,74–0,80). Наиболее распространенным инструментом оказались чат-боты типа ChatGPT (81,8%); инструменты чаще применяются для развития словарного запаса и навыков письма. Воспринимаемая полезность получила наивысшую оценку ($M = 3,80$), простота использования — самую низкую ($M = 3,44$). Полезность положительно связана с намерением использования ($\rho = 0,53$; $p = 0,002$); статистически значимой связи между частотой использования и намерением использования не выявлено. Открытые ответы указали на инфраструктурные барьеры, недоверие к точности ответов и проблемы качества ответов на казахском языке. Обсуждаются рекомендации для программ подготовки учителей иностранных языков.

Ключевые слова: искусственный интеллект; ИИ-инструменты для изучения языка; модель принятия технологий; будущие учителя английского языка; иноязычное образование; ChatGPT; воспринимаемая полезность; намерение использования; ИИ-грамотность;

INTRODUCTION

Artificial intelligence (AI) technologies have been reshaping language education in recent years, and research is only beginning to catch up with practice. A systematic review of AI applications in higher education found rapid technological spread alongside weak pedagogical grounding [1]. Within language education, adaptive systems form one recognisable group of AI-based tools: they adjust task difficulty, content and feedback to the learner's level and responses, and the literature often uses the terms adaptive learning and personalized learning interchangeably [2]. The arrival of generative tools such as ChatGPT then widened the picture considerably and sharpened research interest in foreign language teaching. Researchers have studied the place of

ChatGPT in EFL learners' informal digital learning [3], teachers' views on what such tools can offer [4], and how AI tools affect affective factors related to speaking [5]. In this article the umbrella term AI-enabled language learning tools covers both specialized adaptive applications and general-purpose generative chatbots used for language learning; adaptivity is treated as one salient feature of such tools rather than a defining criterion.

Whether a new technology takes root in education depends above all on whether its users accept it. Acceptance research on generative AI already shows that established models transfer to this new class of tools: studies of university students' uptake of ChatGPT confirm their applicability [6]. The framework applied most often remains the Technology Acceptance Model (TAM). Davis [7] proposed explaining the intention to use a technology through two constructs, perceived usefulness (PU) and perceived ease of use (PEOU). Later extensions [8] and systematic reviews of educational settings [9] support the continuing relevance of TAM for studying how educational technologies are received.

Pre-service teachers occupy a particular position in acceptance research because they encounter AI twice, first as learners and later as professionals who decide whether to bring such tools to their own students. In a study of 452 pre-service teachers at a German university, perceived usefulness ($\beta = 0.501$) and perceived ease of use emerged as the main predictors of the intention to use AI [10]. Initial language teacher education has also begun responding to generative AI: teacher educators report rethinking their courses [11], and intervention studies have sought to build pre-service language teachers' professional generative AI competence [12]. Such work connects to the wider agenda of AI literacy [13] and to the UNESCO AI competency framework for teachers [14]. Survey evidence on how pre-service English teachers themselves accept and use AI-enabled language learning tools nevertheless remains limited, particularly outside East Asian and European contexts.

For Kazakhstan the question carries particular weight. AI development has been declared a state priority, and the Concept for the Development of Artificial Intelligence for 2024–2029 was approved by Government Decree No. 592 of 24 July 2024 [15]. Access to AI tools in the education system keeps expanding, yet empirical evidence on how future foreign language teachers actually use and accept them remains limited. The quality of AI output in Kazakh deserves attention as well: in a recent evaluation conducted in the clinical nutrition domain, ChatGPT-4 outputs in Kazakh performed substantially worse than corresponding English and Russian outputs [16]. How such localization constraints shape learners' acceptance is still poorly documented, particularly for Kazakhstan.

Against this background, the study set out to identify pre-service English teachers' acceptance and use of AI-enabled language learning tools at one Kazakhstani pedagogical university. The research questions and the hypothesis are formulated in the Materials and Methods section.

MATERIALS AND METHODS

The study followed a cross-sectional survey design. Four research questions were posed: (RQ1) which AI-enabled language learning tools students use, how often, and for which language skills; (RQ2) what the levels of the acceptance constructs are, namely perceived usefulness (PU), perceived ease of use (PEOU), and behavioral intention (BI); (RQ3) whether indicators of use are related to the acceptance constructs; (RQ4) what intentions students hold, as future teachers, about applying these tools in their professional work. Within RQ3 one hypothesis was tested: H1, usage frequency is positively related to behavioral intention.

The study involved third- and fourth-year students of the English teacher education programme at one Kazakhstani pedagogical university (convenience sampling). Of 40 distributed questionnaires, 38 were completed and returned (a response rate of 95%). Twenty-two respondents (57.9%) were third-year and 16 (42.1%) fourth-year students; 29 (76.3%) were female and 7 (18.4%) male, one respondent preferred not to indicate gender, and one left the question unanswered. Self-assessed English proficiency (CEFR) was distributed as follows: A2 – 3 (7.9%), B1 – 17 (44.7%), B2 – 15

(39.5%), C1 and above – 3 (7.9%). The screening question showed that 33 respondents had used AI-enabled language learning tools within the previous twelve months and entered the main analysis; the 5 non-users answered only the demographic block and the open-ended question on barriers.

The questionnaire was administered on paper in class. Permission to conduct the study was obtained, and the introductory section of the questionnaire informed respondents about voluntary participation, the anonymity of responses, and the use of data in aggregated form for research purposes only, which served as informed consent.

The questionnaire consisted of six parts: a screening question, a demographic block, a usage profile (a list of tools, frequency, skills, and duration), an acceptance block, a future-teacher block, and two open-ended questions. The screening question offered respondents a working definition, describing AI-based tools that automatically adjust task difficulty, content, or feedback to the learner, and listed examples that included specialized applications and ChatGPT-type chatbots used for language learning. Because the tools respondents actually reported ranged from adaptive applications to general-purpose chatbots, the broader term AI-enabled language learning tools is used in reporting. The items of the acceptance block were adapted from the original constructs of the Technology Acceptance Model [7]: PU with four items, PEOU with four items, and BI with three items, all on a five-point Likert scale (1 – strongly disagree, 5 – strongly agree). Two author-developed additions were included: item PU5 on adaptivity and a future-teacher (FT) block of three items. Neither belongs to the original instrument [7]: PU5 was treated as a separate exploratory item and was not merged into the PU composite, and the FT block was analyzed separately. The items were forward-translated into Kazakh by the author and checked against the original English wording; the full cross-cultural adaptation cycle recommended for self-report measures [17], including back-translation, expert committee review, and pretesting, was not implemented, and the instrument was not piloted before field use. Both points are acknowledged in the Limitations section.

The analysis relied on descriptive statistics (frequencies, percentages, means, and standard deviations), internal consistency of the scales (Cronbach's alpha), and Spearman rank correlations. Composite scores were computed as the mean of the items; a composite was calculated only when at least three of the four PU items, three of the four PEOU items, and all three BI and FT items had been answered. Given the small sample size ($n = 33$), no factor analysis was performed, and non-parametric correlations were used. Apart from the hypothesized H1 test, all correlations were exploratory and are reported with unadjusted p-values. The analysis was carried out in Python 3 with the pandas and SciPy libraries.

The two open-ended questions were analyzed through inductive content analysis. All responses were read in full and assigned short descriptive codes; codes recurring across responses were grouped into broader themes. Coding was performed on the original Kazakh responses, and illustrative quotations were translated into English by the author for reporting. Coding was carried out by the author alone; no second coder was involved, so intercoder reliability could not be computed. This is acknowledged in the Limitations section.

RESULTS

Usage profile (RQ1). Among users ($n = 33$) the most widespread tools were ChatGPT/Gemini-type chatbots used for language learning (27 respondents, 81.8%), followed by Duolingo (17; 51.5%) and Quizlet (17; 51.5%), ELSA Speak (9; 27.3%), Memrise (5; 15.2%), and Busuu (2; 6.1%); Grammarly, Cake (twice), and DeepL Write were named under the option 'other'. The largest groups by frequency used the tools about once a week (13; 39.4%) or several times a week (11; 33.3%); two respondents (6.1%) used them daily. As for duration, 11 respondents (33.3%) had used the tools for 6–12 months, 8 (24.2%) for more than a year, 9 (27.3%) for 3–6 months, and 5 (15.2%) for less than three months. The tools were applied most often to vocabulary (22; 66.7%), writing (20; 60.6%), speaking practice (19; 57.6%), and grammar (18; 54.5%); pronunciation was named least often (11; 33.3%). A detailed usage profile is presented in Table 1.

Table 1. Usage profile of AI-enabled language learning tools (n = 33)

Indicator	Category	n (%)
Tools (multiple choice)	ChatGPT/Gemini (chatbot)	27 (81.8)
	Duolingo	17 (51.5)
	Quizlet	17 (51.5)
	ELSA Speak	9 (27.3)
	Memrise	5 (15.2)
	Busuu	2 (6.1)
	Other (Grammarly, Cake, DeepL Write)	4 (12.1)
Frequency	Daily	2 (6.1)
	Several times a week	11 (33.3)
	About once a week	13 (39.4)
	Several times a month	6 (18.2)
	Less often	1 (3.0)
Duration	Less than 3 months	5 (15.2)
	3–6 months	9 (27.3)
	6–12 months	11 (33.3)
	More than a year	8 (24.2)

Acceptance levels (RQ2). All multi-item scales showed satisfactory internal consistency ($\alpha \geq 0.70$; Table 2). Perceived usefulness received the highest composite rating ($M = 3.80$, $SD = 0.60$), while perceived ease of use was rated comparatively low ($M = 3.44$, $SD = 0.68$), with the weakest single item concerning the ease of finding the needed function ($M = 3.09$). Behavioral intention ($M = 3.48$, $SD = 0.74$) and future-teacher intention ($M = 3.53$, $SD = 0.85$) were above the scale midpoint. The exploratory adaptivity item PU5 received the highest rating among the usefulness statements ($M = 3.97$, $SD = 0.85$); it was analyzed as a separate item and was not merged into the PU composite.

Table 2. Descriptive statistics and reliability of the scales (users, n = 33)

Scale / item	Items	Cronbach's alpha	M	SD	n
Perceived usefulness (PU)	4	0.74	3.80	0.60	33
PU5: adaptivity (exploratory item)	1	—	3.97	0.85	33
Perceived ease of use (PEOU)	4	0.77	3.44	0.68	33
Behavioral intention (BI)	3	0.80	3.48	0.74	31
Future-teacher intention (FT)	3	0.76	3.53	0.85	31

Relations between use and acceptance (RQ3). Hypothesis H1 was not supported: the association between usage frequency and behavioral intention did not reach statistical significance ($\rho = 0.26$, $p = 0.150$, $n = 31$). The associations of usage duration and tool range with the acceptance constructs also failed to reach significance (all $|\rho| \leq 0.28$, $p > 0.05$). At the same time, the relations among the constructs were broadly consistent with selected TAM relationships: a moderate positive association was recorded between PU and BI ($\rho = 0.53$, $p = 0.002$, $n = 31$), and positive associations were found between PU and PEOU ($\rho = 0.44$, $p = 0.010$, $n = 33$) and between PU and FT ($\rho = 0.40$, $p = 0.027$, $n = 31$). In exploratory analyses, the adaptivity item PU5 was also positively associated with BI ($\rho = 0.42$, $p = 0.020$, $n = 31$). These additional correlations were exploratory and are reported with unadjusted p-values (Table 3).

Table 3. Spearman rank correlations, ρ (n)

Variable	1	2	3	4	5
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1. Usage frequency	—				
2. PU	−0.02 (33)	—			
3. PU5 (item)	−0.14 (33)	0.71** (33)	—		
4. PEOU	−0.01 (33)	0.44* (33)	0.23 (33)	—	
5. BI	0.26 (31)	0.53** (31)	0.42* (31)	0.31 (31)	—
6. FT	0.06 (31)	0.40* (31)	0.38* (31)	0.14 (31)	0.31 (30)

*Note: * $p < 0.05$; ** $p < 0.01$; pairwise n in parentheses. Correlations other than the H1 test are exploratory; p -values are unadjusted.*

Open-ended responses (complementing RQ1 and RQ4). Four themes were identified in the answers about benefits (29 responses): adaptivity and personal pace ('tasks that match my level', 'I train my weak points more', 'I choose the difficulty myself'); immediate feedback and error analysis ('I notice my mistakes right away', 'I understand why it was wrong'); time saving and accessibility; and contextual explanation with examples. Four themes were identified in the answers about barriers (32 responses, including non-users): infrastructural and financial barriers (unstable internet, paid features, advertising); distrust of answer accuracy ('I am afraid it gives wrong answers', 'it may turn out wrong when I check later'); the quality of Kazakh-language adaptation ('the Kazakh answers are not accurate', 'the Kazakh examples feel unnatural', difficulty with English-only interfaces); and self-regulation difficulties (distraction, the risk of depending on ready-made answers). The reasons given by the five non-users were not knowing where to start, the sufficiency of the teacher's materials, unstable internet, fear of wrong answers, and the absence of need.

DISCUSSION

Several findings deserve comment. The usage profile, to begin with, was dominated by general-purpose ChatGPT/Gemini-type chatbots used for language learning (81.8%) rather than specialized adaptive applications. What respondents experience as adaptivity is therefore mostly dialogic, not algorithmic level adjustment: explanation on request, examples, reformulation. The open-ended answers make this concrete ('if I do not understand, it explains again in other words', 'I can ask my own question freely'), and the picture fits the rapid uptake of generative chatbots among university students reported elsewhere [6].

A second pattern concerns the balance of the acceptance constructs. Perceived usefulness was rated highest among the composites ($M = 3.80$) and ease of use lowest ($M = 3.44$), with the weakest single item concerning the ease of finding the needed function ($M = 3.09$). Students acknowledge the value of the tools yet still find using them effortful, and the open-ended answers suggest why: English-only interfaces, paid features and limits, and the difficulty of choosing among many platforms. The leading role of usefulness is consistent with the TAM literature [8], [10]. The exploratory adaptivity item, meanwhile, received the highest rating among the usefulness statements ($M = 3.97$), which suggests that adaptivity itself is a salient source of perceived value for this group; the observation requires confirmation with a validated multi-item measure.

Hypothesis H1, in turn, was not supported: no significant association emerged between usage frequency and behavioral intention. Two readings are possible. The sample size allowed the detection of moderate-to-strong associations only, so nothing can be concluded about the absence of a weak association. At the same time, the relatively even level of acceptance across usage intensities suggests that even infrequent users value the tools. The relations among the constructs (PU–BI: $\rho = 0.53$; PU–PEOU: $\rho = 0.44$) were broadly consistent with selected TAM relationships even in a small sample.

A locally salient finding concerned the quality of AI output in Kazakh. Among the barriers, students noted inaccurate Kazakh answers and unnatural Kazakh examples, alongside a broader distrust of answer accuracy ('I am afraid it gives wrong answers', 'it may turn out wrong when I check later'). These perceptions are consistent with evidence of weaker Kazakh-language performance reported for ChatGPT-4 in another applied domain [16], although direct evidence

from language-learning contexts remains limited. In the acceptance literature, evidence on the localization quality of less-resourced languages as an acceptance barrier remains limited. With AI development now a state priority in Kazakhstan [15], the quality of Kazakh-language output may well shape how successfully AI tools enter Kazakh-language educational settings.

Finally, the future-teacher block showed professional intention above the scale midpoint ($M = 3.53$), and students themselves recognized the need for special teacher preparation (FT3: $M = 3.47$). The findings suggest that future foreign language teachers need targeted preparation in selecting AI-enabled tools, critically evaluating the quality of their output, particularly in Kazakh, and integrating them methodically into teaching. These skills are core elements of AI literacy [13], [14] and align with current developments in initial language teacher education [11], [12].

Limitations. The study has several limitations. Convenience sampling and the single-institution context do not allow generalization of the results. The sample included only third- and fourth-year students, and its gender composition was asymmetric (76.3% female). Given the small sample size ($n = 33$), the study had limited power to detect weak correlations, so null associations should be interpreted cautiously. The cross-sectional design gives no grounds for causal claims. The Kazakh version of the instrument was forward-translated without back-translation, expert committee review, or pretesting [17], was not piloted, and did not undergo full psychometric validation (no factor analysis was performed). Open-ended responses were coded by a single coder, so intercoder reliability could not be established. The screening definition combined specialized adaptive systems with general-purpose AI chatbots used for language learning; consequently, the operational category was broader than strict definitions of adaptive learning. All indicators were based on self-report.

CONCLUSION

The study provides an initial empirical account, from one Kazakhstani institution, of pre-service English teachers' acceptance and use of AI-enabled language learning tools. Use of these tools was common among the respondents, with general-purpose chatbots predominating; the respondents considered the tools useful while rating ease of use comparatively low. The acceptance constructs were interrelated in a way broadly consistent with TAM, whereas no significant association was found between usage frequency and intention. Among the barriers, alongside infrastructural and financial factors, distrust of answer accuracy and the quality of Kazakh-language adaptation occupied a distinct place.

For teacher education programmes, the results point to the need to develop AI literacy purposefully, from tool selection to critical evaluation of output quality and methodological integration. Future work could validate the Kazakh version of the instrument on a larger sample with factor analysis, compare several universities, apply experimental and longitudinal designs to the influence of use on learning outcomes, and evaluate the quality of AI output in Kazakh in pedagogical contexts systematically.

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