JSSER
www.jsser.org
Journal of Social Studies Education Research
Sosyal Bilgiler Eğitimi Araştırmaları Dergisi
2026:17 (2), 375-405

# Integration of AI-Based Tools in Teaching Ethnocultural Units: A Qualitative Comparative Study Between Kazakh and English-Language Learners

Didar Ryskulbek[1], Saule Daurenbek[2], Tynyshtyk Yermekova[3] & Aymeken Dossmurzaeva[4]

## Abstract

The use of AI translation tools in foreign language learning is growing due to the rapid adoption of AI technologies in educational settings. There is limited research on how AI translations influence students' understanding of ethnocultural expressions and the development of their intercultural sensitivity. This study investigates how students understand ethnocultural expressions in AI-translated texts, identifies cultural errors they find, and examines how they verify and correct these translations. A qualitative research design utilizing content analysis was employed. The study involved 20 university students divided into two groups: Kazakh (n=10) and English (n=10). Students used a variety of AI tools to translate texts that contained ethnocultural units. Semi-structured interviews were conducted post-assignments to assess students' perceptions of the cultural appropriateness of translation, identify biases, and evaluate verification strategies. Cross-case content analysis was employed to examine the collected data. The findings showed that most students recognized the literal nature of AI translations and the loss of cultural nuances, particularly in idioms, proverbs, and metaphors. Patterns in the data suggested that Kazakh participants often drew on prior cultural experience when interpreting ethnocultural expressions, whereas English-language participants more frequently referred to analytical and contextual strategies. The most common verification strategies were comparing several AI systems, back-translating, analyzing context, and consulting additional sources. Additionally, engaging with AI translations fostered a critical mindset toward automated translation tools and raised cultural awareness. Overall, AI translation supports language learning and intercultural reflection, but its limitations in conveying deep cultural meaning require pedagogical guidance. Future research should expand sample sizes, examine different educational contexts, and incorporate quantitative measures of intercultural competence.

***Keywords:*** *AI-assisted learning, ethnocultural units, intercultural communicative competence, cultural meaning in translation, qualitative analysis*

[1] *Ph.D, Kazakh National Women's Teacher Training University, Kazakhstan, ryskulbek.didar@mail.ru*
[2] *Ph.D, Abai Kazakh National Pedagogical University, Kazakhstan, s.daurenbek@abaiuniversity.edu.kz (corresponding author)*
[3] *Doctor of Philological Sciences, Kazakh National Women's Teacher Training University, Kazakhstan, yermekovat@gmail.com*
[4] *Candidate of Pedagogical Sciences, K. Zhubanov Aktobe Regional University, Kazakhstan, ken_tina@mail.ru*

## Introduction

Artificial intelligence has been rapidly developing in the fields of intercultural communication, education, science, and language teaching. In the field of language teaching, AI is distinguished not only by the use of linguistic codes but also by the introduction of cultural codes into computer models (Bhargava et al., 2023). In this regard, some scholars argue that AI should not be limited to lexical-grammatical codes, but also include cultural codes (Messner, 2022; Abhivardhan & Agarwal, 2019). This shift is reflected in modern multilingual and deep learning systems that aim to capture complex linguistic and cultural patterns (Gromann, 2020).

The role of AI in intercultural communication is closely related to language systems that can work with cultural codes. Recent developments include AI-assisted digital cultural heritage systems and information-based cultural mapping tools that enable the visualization and analysis of cultural knowledge (Mitsa et al., 2023). Accordingly, AI may be able to distinguish cultural similarities and differences through computer modeling (Espín-León et al., 2020). However, despite these technological developments, the educational and pedagogical implications of AI in cultural language learning remain underexplored.

Ethnocultural units are culture-specific linguistic expressions, such as idioms, proverbs, metaphors, and words that carry cultural significance. They convey cultural values, traditions, and perspectives, and understanding them goes beyond their literal meaning. These units highlight an important link between language and culture. Interpreting them relies on context, practical understanding, and cultural insight rather than simple translation.

Despite the technological potential of AI, current systems are focused on algorithmic efficiency rather than on cultural and educational applications. As a result, AI-generated translations may fail to preserve culturally embedded meanings, particularly for ethnocultural units fully. This limitation highlights concerns regarding cultural distortion and incomplete interpretation in AI-mediated language processing. Previous research has also emphasized that AI-based systems may produce linguistically correct but culturally inadequate outputs due to their reliance on statistical rather than culturally grounded representations of meaning (Gromann, 2020).

From an educational perspective, this raises important questions about learners' engagement with AI-generated cultural content. While AI tools are increasingly used in language learning environments, little is known about how learners interpret ethnocultural meanings, detect cultural inaccuracies, or evaluate the adequacy of translations in AI-mediated tasks. This gap is particularly evident in pedagogical contexts where learners are expected to develop intercultural awareness and interpretive competence through interaction with AI-generated texts.

While AI-based semantic models, digital heritage, and computer-based cultural identity models are rapidly developing, empirical research on translating ethnocultural units via AI in the context of a personalized educational approach is almost nonexistent. It should be emphasized that a lack of empirical studies on students' perceptions of this process is also evident.

To fill this gap, a qualitative comparative study was undertaken to analyze how Kazakh- and English-language students perceive, comprehend, and critique ethnocultural units generated by AI tools. Relying upon the theoretical framework of intercultural communicative competence (ICC), the study concentrates on students' interpretative procedures, strategies for identifying errors, and cultural consciousness demonstrated when dealing with AI-generated translations. Thus, the study is guided by the following research questions:

1. How do English and Kazakh language learners comprehend and analyze ethnocultural elements in texts that AI translates?
2. How well can students identify errors or cultural misrepresentations in translations of ethnocultural units produced by AI?
3. Which AI translation tools do learners think exhibit better linguistic and cultural adequacy?
4. How does the Kazakh-language group's engagement with AI-translated ethnocultural units affect students' interpretations, correction techniques, and cultural comprehension compared to the English-language group?

## Theoretical Framework

### Conceptualization of Ethnocultural Units in Artificial Intelligence Contexts

Ethnocultural units are the primary subject of linguistics and are closely connected to cultural values, worldviews, and traditions (Abdujabarova & Nassiri, 2022; Kazangapova et al., 2024). In the present study, ethnocultural units are understood as linguistic expressions unique to particular cultures, including proverbs, idioms, metaphors, and culturally charged lexical items. These units are examined in relation to the process of interpreting them for purposes of evaluation in AI-generated translations. They encompass verbal, nonverbal, cultural, and symbolic expressions and beliefs unique to a particular cultural context. Previous classifications distinguish ethnocultural units by genre, national mentality, belief systems, and philosophical knowledge (Issabekova et al., 2024), as well as by oral, mental, symbolic, and non-verbal forms (Ternavskaya & Bogdanova, 2023; Zhunussova et al., 2026).

Ethnocultural units such as idioms, proverbs, metaphors, and culturally loaded lexical items encode culturally specific meanings that cannot be understood through literal translation alone. Their interpretation requires contextual, pragmatic, and cultural awareness, as they reflect implicit meanings, shared assumptions, and communicative intentions embedded in a particular sociocultural environment.

Given the culturally embedded nature of ethnocultural units, recent advances in AI have increasingly emphasized the need for culturally informed intelligent systems rather than purely technocentric approaches. Bhargava et al. (2023) argue that modern AI systems must move beyond the surface-level of multilingualism and incorporate ethnolinguistic principles to work effectively in intercultural communication contexts. However, despite these developments, AI systems remain largely optimized for linguistic accuracy rather than culturally grounded interpretation, raising concerns about their ability to represent culturally embedded meanings accurately.

Messner (2022) introduces the concept of machine inculturation, arguing that AI systems that are trained on data from one cultural context do not generalize to others. This suggests that cultural knowledge cannot be considered a neutral or universal element. Similarly, Abhivardhan and Agarwal (2019) emphasize that cultural awareness is essential in machine learning systems to avoid ethical and interpretive failures in multilingual and multicultural environments.

Beyond translation accuracy, studies on computational modeling of cultural codes demonstrate both the potential and limitations of AI systems. Espín-León et al. (2020) developed an AI-based method to calculate cultural identity distances between indigenous Amazonian communities, demonstrating that computational models can identify cultural differences across groups. However, limited attention has been paid to how such advances can be applied in educational contexts, particularly in learners' engagement with AI-generated cultural texts and the translation of ethnocultural units.

**Artificial Intelligence and Cultural Representation**

Translating culture-bound terms poses considerable challenges for artificial intelligence-based language translation. Culture-specific terms require more than lexical equivalence; they involve context, history, and value-based aspects (Bhargava et al., 2023). Nevertheless, neural machine translation (NMT) and large language models (LLMs) depend more on probabilistic modeling than on culturally based semantics.

Thus, the output from such tools might be linguistically correct but not culturally appropriate, especially when translating cultural idioms that have no direct equivalents in other languages. Gromann (2020) emphasizes that such AI systems are not capable of transcultural meaning because they rely on a co-occurrence-based learning approach rather than a culturally aware one.

**Artificial Intelligence, Cultural Coding, and Translation Limitations**

To address these limitations, recent research has focused on integrating cultural knowledge into AI systems through approaches such as machine acculturation, in which models are trained on both linguistic and cultural data (Abhivardhan & Agarwal, 2019; Hamd et al., 2026; Messner, 2022). These approaches aim to reduce cultural bias and enhance contextual sensitivity in machine translation.

AI systems have demonstrated the ability to identify cultural and linguistic patterns computationally (Espín-León et al., 2020; Koyanbekova et al., 2026), and interactive tools such as dialect maps support ethnocultural documentation (Mitsa et al., 2025). Additionally, knowledge graph–based approaches enhance the representation of semantic and cultural relationships by linking lexical items with their cultural contexts (Vossen, 1998).

Despite these developments, much research remains system-focused and offers little insight into how human users, particularly language learners, understand AI-created culture in educational contexts. Thus, there is a need for research focused on studying learners' interactions with AI-produced ethnoculture.

From an educational perspective, AI-based translation of ethnocultural units presents challenges related to learners' interpretation, error detection, and cultural awareness. Although students increasingly rely on AI tools to access culturally rich content, limited research has examined how learners evaluate the adequacy of translations, recognize cultural inaccuracies, and interpret AI-generated cultural meanings. Within this context, the Cultural Intelligence Technology Model highlights the importance of cultural awareness, interpretation ability, and technological competence in AI-mediated language learning, highlighting the need for pedagogically oriented research on AI-mediated cultural learning (Anas et al., 2025; Kalymova et al., 2026; Vedaschi Ozzola, 2025).

### Knowledge Graphs and Semantic Modeling of Cultural Information

Recent studies highlight the importance of incorporating knowledge graphs and semantic networks to create culturally sensitive AI translation. The two techniques allow for the association of terms within their cultural context, leading to culturally informed rather than merely translated products (Vossen, 1998). Semantic modeling, combined with knowledge graph technologies and artificial intelligence, can improve the representation of cultural knowledge in digital environments (Felicetti et al., 2025). Nevertheless, the existing literature remains biased towards the AI side and provides insufficient information on how learners perceive such cultural translations.

### Intercultural Communicative Competence and AI-Mediated Cultural Learning

Advances in digital technologies and artificial intelligence (AI) have significantly reshaped foreign language education by expanding learners' access to multilingual and multicultural content. Using a language means correctly recognizing and communicating the culture and cultural values of the nation that speaks that language. In this context, this shift has reinforced the importance of Intercultural Communicative Competence (ICC) as a central pedagogical construct in language education (Byram, 1997). Intercultural communicative competence entails behaving appropriately in social settings, knowing oneself and others, and communicating effectively across contexts (Byram, 1997; Deardorff, 2006).

Byram (1997) identifies the core components of intercultural communication as knowledge, attitudes, interpreting and relating skills, discovery and interaction skills, and critical cultural awareness. Similarly, Deardorff (2006) states that intercultural communication competence is developed not solely through learning but through interaction, reflection, and experience. As this suggests, cultural knowledge does not develop merely through learning a language; rather, it requires awareness and self-reflection.

In line with this understanding, intercultural communicative competence relies strongly on ethnocultural units such as idioms, proverbs, and cultural expressions, which carry cultural values and require contextual and pragmatic interpretation. These units should be treated as learning objectives, as they develop intercultural skills, enrich learners' identities (Norton, 2013; Wolff & Borzikowsky, 2018), and support awareness of cultural misunderstandings (Sobkowiak, 2019; Trede et al., 2013).

The Integration of AI tools into language learning environments provides learners with access to culturally rich texts but also introduces interpretive risks. AI-generated translations may simplify or distort culture-specific meanings, limiting the accuracy of cultural transfer. Consequently, linguistic equivalence does not necessarily ensure cultural equivalence, which may result in what Carter (2001) defines as “false cultural competence.”

Therefore, learners’ ability to interpret, evaluate, and critically reflect on AI-generated cultural content is essential for developing intercultural competence. Despite increasing use of AI tools, research on their educational impact remains limited, particularly regarding learner interpretation, error detection, and comparison of cultural meanings across systems (Bhargava et al., 2023; Messner, 2022).

## Method

### Research Design

This study employed a qualitative comparative case study design to explore how learners interpret and engage with ethnocultural units presented through AI-generated translations. A qualitative approach is appropriate because it seeks to understand learners' perceptions and meaning-making strategies regarding culturally rich AI-mediated texts (Creswell, 2009).

Comparative case study design focuses on similarities and differences between two groups of learners while interacting with AI-translation tools. Each group presented a case, presented by language of instruction, linguistic background, and engagement with AI-translated ethnocultural texts. The design enabled understanding of cultural interpretation, error detection, and correction strategies in the context of AI tools.

The analysis of ethnocultural units was guided by the operational definition presented in the theoretical framework, ensuring alignment between conceptualization and empirical procedures. The methodology integrated ethnocultural unit theory, Intercultural Communicative Competence (ICC), and the Cultural Intelligence Technology Model. Ethnocultural unit theory guided identification tasks, ICC informed interpretive coding of learners' responses, and the Cultural Intelligence Technology Model shaped the evaluation of learners' interaction with AI outputs and correction strategies.

These constructs were operationalized through learners' engagement with AI-generated translations, including interpreting ethnocultural expressions, identifying cultural misrepresentations, evaluating translation adequacy, and comparing outputs from ChatGPT, Google Translate, and Yandex Translate. Interview responses captured intercultural awareness, interpretation strategies, and error detection processes. ICC components (knowledge, attitudes, interpretation, and critical cultural awareness) informed the coding categories. At the same time, the Cultural Intelligence Technology Model guided the analysis of learners' interaction with AI-generated cultural content, particularly in evaluating and correcting ethnocultural meanings. This ensured alignment between the theoretical framework and empirical procedures.

**Participants**

The participants in the study were undergraduate students at Kazakh National Women's Teacher Training University in Kazakhstan. Purposive sampling was used to conduct a qualitative comparison between Kazakh language learners and English language learners who were engaged in learning culturally rich texts with the support of AI-based translation tools. The sample was divided into 2 groups: 10 Kazakh-language learners, whose language of instruction was Kazakh; 10 English-language learners, who had courses in English, with a minimum English proficiency level of B2 as indicated by the institution. The CEFR B2 level was determined based on the university's standardized internal English placement test, which assesses reading, writing, listening, and grammar proficiency aligned with CEFR descriptors.

All participants had experience using AI translation tools, such as ChatGPT, Google Translate, and Yandex Translate, for translation and learning, particularly for texts containing idioms, proverbs, and culturally based expressions. This indicates that participants had prior experience with AI-based translation tools and related learning practices.

The study's sample size was appropriate for the data analysis procedure. According to Creswell (2009), a range of 5-25 participants was sufficient for qualitative data saturation, especially for the semi-structured interview. Based on this, the selected sample size was enough to analyze how learners interpret and engage with ethnocultural units presented through AI-generated translations. In the study, the researchers carefully followed all ethical principles. Participants were given informed consent and were aware of the study's purpose. Participants' responses were transcribed and analyzed. The data were presented using pseudonyms such as "K1", "K2", "K3" for the Kazakh group and "E1", "E2", "E3", etc. for the English group during transcription and reporting. Institutional permission for conducting the study was obtained from the university ethics committee.

**Data Collection Tools**

To achieve the aim, various data tools were applied to answer the research questions. Firstly, participants were given ethnocultural texts including idioms, proverbs, and specific contexts. Ethnocultural units were identified based on their cultural specificity, non-literal meaning, and contextual interpretation, in line with the theoretical framework.

During the translation process, AI tools such as ChatGPT, Google Translate, and Yandex Translate were utilized. Participants were also asked to compare translations generated by ChatGPT, Google Translate, and Yandex Translate and identify the tool that provided the most linguistically and culturally appropriate output. Secondly, participants completed evaluation tasks to analyze the translation and find cultural inaccuracies or distortions. These tasks were designed to evaluate learners' cultural awareness and interpretive strategies.

A semi-structured interview form was used to analyze learners' perceptions. Four experts assessed content validity during the interview design process. The experts evaluated the questions for clarity and alignment with the study's aim and the research questions. The revision was made in accordance with the experts' feedback. After completing all the steps, a semi-structured interview form was administered to the study sample.

**Data Collection**

The data collection procedure was carried out in several stages. Before data collection, texts containing ethnocultural units characterized by proverbs, concepts, and idiomatic verbs were designed. The texts were selected because of their suitability for analysis by AI-assisted translation of ethnocultural units. Each text contained approximately 8-10 ethnocultural units and ranged in length from 150 to 200 words.

The texts were translated into Kazakh and English using ChatGPT, Google Translate, and Yandex Translate. To preserve the originality of the AI-based translations, the teachers made no corrections to them.

During the study, participants were given AI-based translated texts. They analyzed the texts individually. Participants were asked to carefully read the translated texts, identify ethnocultural units, analyze their meanings, and evaluate the translations' accuracy in terms of socio-cultural context. Participants were also encouraged to compare AI-generated translations with the original texts when necessary.

Following the textual analyses, semi-structured interviews were conducted to examine participants' interpretations of ethnocultural units, identification of cultural inaccuracies, and perceptions of AI-based translation tools.

All participants' responses were transcribed for qualitative data analysis. Ethical principles were strictly followed, and participants were assigned pseudonyms to ensure confidentiality. In this case, all steps were considered during the procedure, enabling the researchers to analyze the cases using AI-based tools and answer the research questions.

**Data Analysis**

Participants' responses were analyzed using content analysis. Content analysis is a systematic method for interpreting data to draw meaningful conclusions (Saldaña, 2021). For content analysis, the MaxQDA program was used. Cross-case analysis was conducted to identify learners' systematic perceptions, interpretations, critical evaluations, and correction strategies regarding AI-generated translations of ethnocultural units.

All interview recordings were transcribed and imported into MaxQDA to facilitate systematic coding, organization, and cross-group comparison. During coding, all transcripts were analyzed to develop a holistic understanding of the data. The codes were reviewed and grouped into categories to identify the connection. The gained categories were then transferred to themes reflecting learners' interpretations and correction strategies for AI-generated translation.

The cross-case analysis was conducted to analyze similarities and differences between the two groups. Additionally, this approach was used to explore how themes appeared across the two groups. This comparison helps identify group-specific patterns in understanding, error detection, and correction strategies for evaluating AI translations.

The reliability of the content analysis was assessed through several strategies. Firstly, the coding process was conducted independently by the researchers. The MaxQDA program provided a transparent system for coding, category development, and theme organization, thereby increasing the objectivity of the data analysis process. The reliability formula by Miles and Huberman (1994) was utilized. The coded data was compared using the formula. Accordingly, the intercoder agreement was .93 for Kazakh-language learners and .86 for English-language learners. The results show that the coding process is reliable, as indicated by the coefficient (Miles & Huberman, 1994).

## Findings

The following section presents the results related to the research questions. Students learning Kazakh and English were asked questions aimed at assessing their understanding and interpretation of ethnocultural units, identifying errors in AI-based translations of ethnocultural units, and evaluating the AI tools in terms of translation accuracy and correction strategies. An analysis of the results by sub-question is presented below.

### Findings for Research Question 1: How Do English and Kazakh Language Learners Comprehend and Analyze Ethnocultural Elements in Texts That AI Translates?

In the study, the first question asked of students during the interview was: *"How did you understand the meaning of ethnocultural units in the text translated using AI?"* Table 1 presents the codes, number of codes, categories, and themes obtained from the content analysis.

**Table 1**

*Students' Opinions on Understanding AI-Translated Ethnocultural Units*

| Theme | Questions | Category | Code | Number of codes | Participant |
|---|---|---|---|---|---|
| Understand the meaning of ethnocultural units ($n$=20) | "How did you understand the meaning of ethnocultural units?" ($n$=20) | Contextual Interpretation ($n$=5) | Deriving meaning from the textual context | 5 | K1, K4, K5, E5, E7 |
| | | Cultural Background Experience and Meaning Reconstruction ($n$=15) | Prior cultural knowledge | 7 | K3, K6, K7, K10 E3, E4 |
| | | | From the literal meaning to the cultural | 3 | K2, K9, E1 |
| | | | Comparison with L1 | 3 | E6, E8, E9 |
| | | | Connection with experience | 2 | K8, E10 |

*Note.* K = Kazakh-language group; E = English-language group.

As Table 1 shows, students' responses were divided into two categories: contextual interpretation ($n$=5) and cultural experience and meaning reconstruction ($n$=15). Students' responses indicate multiple codes related to cultural experience and meaning reconstruction ($n$=15). This is explained by the fact that culture is linked to the sociocultural environment and clearly influences a student's educational and cognitive background, their native language, and life experiences. This also shows that these factors influence the understanding of ethnocultural units in AI-translated texts. In particular, prior cultural knowledge ($n$=7) was cited as one of the most common reasons, particularly among several students in the Kazakh group. For example, K3 stated, *"Without cultural knowledge of the phrase 'tayaq tastam', it is difficult to understand its depth."* Some students in the English group reported comparing the target language with their native language when interpreting ethnocultural units in AI-translated texts (*n*=3). For example, student E6 stated, *"The ethnocultural meaning of the codes was not always obvious, so I compared their meanings with my native language."*

The second question asked of the students was: *"To what extent do you think the translation conveyed the cultural meaning of the expressions, not just their literal meaning?"* The results of the content analysis, including themes, categories, and codes, are presented in Table 2.

**Table 2**

*Students' Perceptions of Cultural Meaning Conveyance in AI-Translated Ethnocultural Units*

| Theme | Questions | Category | Code | Number of codes | Participant |
|---|---|---|---|---|---|
| Understand Cultural Meaning Conveyance in AI-Translated Ethnocultural Units (*n*=20) | "To what extent do you think the translation conveyed the cultural meaning of the expressions, and not just their literal meaning?" (*n*=20) | Full Comprehension (*n*=4) | Correct interpretation | 4 | K1, K5 E5, E7 |
| | | Partial Comprehension (*n*=11) | Partial clear | 11 | K2, K3, K4 K9, K10 E1, E3, E4 E6, E9, E10 |
| | | Misunderstanding (*n*=5) | Misinterpreted | 5 | K6, K7, K8 E2, E8, |

*Note.* K = Kazakh-language group; E = English-language group.

Table 2 presents student responses, grouping them into three categories based on a common theme. AI-based tools appeared to partially convey the cultural meaning of ethnocultural units (*n*=11); in several cases, the cultural meanings of the units were misinterpreted (*n*=5); and in a limited number of cases, correct interpretations were produced (*n*=4). These findings suggest that AI-based tools may not consistently capture the full cultural meaning of ethnocultural units, and learners across both groups tend to rely on their cultural experience and existing knowledge when interpreting such translations.

**Findings for Research Question 2: How Well Can Students Identify Errors or Cultural Misrepresentations in Translations of Ethnocultural Units Produced By AI?**

To analyze inaccuracies or identified cultural biases in AI-assisted translations, a third question was asked: *"Have you noticed any cultural inaccuracies or biases in AI-assisted translations? Provide an example."* Students' responses were analyzed by areas of inaccuracy using the provided examples. The frequencies by category and code are presented in Table 3.

**Table 3**

*Students' Perceptions of Cultural Inaccuracies in AI Translations*

| Theme | Questions | Codes | Number of codes | Participant |
|---|---|---|---|---|
| Detection of Cultural Inaccuracies in AI Translations (*n*=20) | "Have you noticed any cultural inaccuracies or biases in translations performed using AI? Provide an example." (*n*=20) | Literal translation | 7 | K1, K3, K7 K8, E1, E3, E4 |
| | | Loss of cultural meaning | 6 | K4, K5, K10 E2, E9, E10 |
| | | Contextual omission | 5 | K6, K9, E5 E6, E7 |
| | | Cultural reduction | 2 | K2, E8 |

*Note.* K = Kazakh-language group; E = English-language group.

According to Table 3, several students (*n*=7) identified literal translation as a frequent type of error when translating ethnocultural units. For example, K1 stated: *"Yes, the cultural unit 'Tusau Kesu' was translated literally as 'the bonds were cut', and its figurative meaning was lost."*

Loss of cultural context was also reported by several students (*n*=6) as a recurring issue in AI-based translations of ethnocultural units. For instance, E2 noted: *"Some phrases sounded correct, but did not reflect cultural specificity. For example: "Toi bastar."*

Across responses, different tendencies were observed in how learners described translation issues. Some Kazakh-language students tended to emphasize the loss of cultural and historical context. In contrast, some English-language students more often referred to the loss of symbolic meaning in AI-generated translations. The main codes for analyzing inaccuracies or identifying cultural errors in AI-based translations are shown in Figure 1.

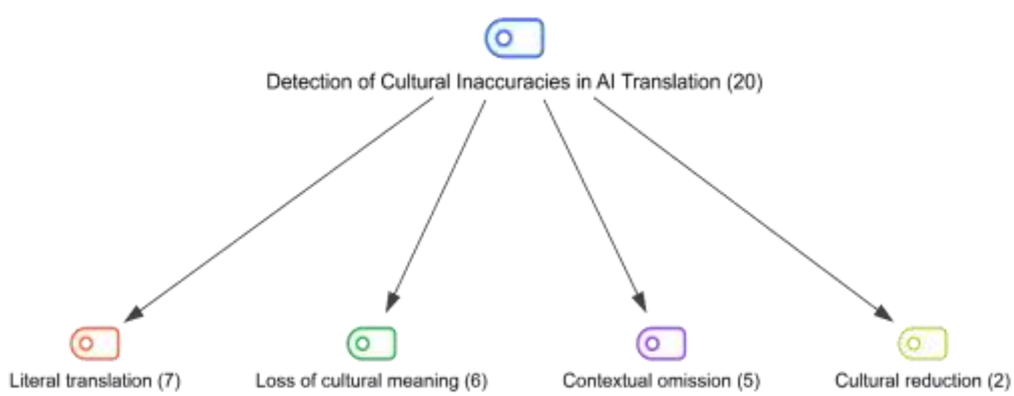


***Figure 1. Hierarchical Codes Model Regarding the Perceptions of Cultural Inaccuracies in AI Translations***

As shown in Figure 1, a total of four main codes were identified through content analysis on the topic *"Detection of Cultural Inaccuracies in AI Translations."* The most frequently occurring codes included literal translation, loss of cultural meaning, contextual omission, and reduction in cultural depth.

The frequency of codes suggests that loss of cultural, historical, and contextual meaning was among the current issues in AI-generated translations of ethnocultural units. This suggests that AI systems may have difficulty consistently capturing the full semantic depth of culturally embedded expressions.

The fourth question asked of students was: *"How did you determine that a translation was incorrect or not culturally appropriate?"* The results of the content analysis, including codes, are presented in Figure 2.

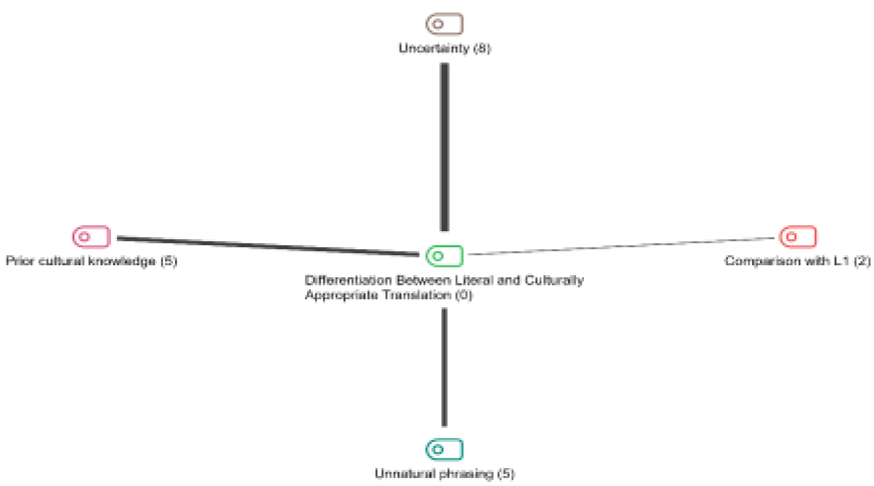


***Figure 2. Codes Segment Model Regarding the Identifying Literal and Culturally Appropriate Translations***

Based on Figure 2, the data are organized around a central category that links the four identified codes. In this structure, a main theme functions as an overarching framework that brings together the individual codes. The relationships between the codes are not explicitly directional; rather, each code is connected through its relation to the central category. Further details of the analysis of students' responses are presented in Table 4.

**Table 4**

*Students' Perceptions about the Determinization of Incorrect Translations*

| Theme | Questions | Codes | Number of codes | Participant |
|---|---|---|---|---|
| Differentiation between Literal and Culturally Appropriate Translation (*n*=20) | "How did you determine that a translation was incorrect or not culturally appropriate enough? " (*n*=20) | Uncertainty | 8 | K2, K5, K8 E1, E3, E6 E9, E10 |
| | | Comparison with L1 | 2 | K9, E7 |
| | | Unnatural phrasing | 5 | K3, K7, E2 E4, E8 |
| | | Prior cultural knowledge | 5 | K1, K4, K6 K10, E5 |

*Note.* K = Kazakh-language group; E = English-language group.

As shown in Table 4 within the theme *"Differentiation between Literal and Culturally Appropriate Translation"* (*n*=20), four main codes were identified in response to the question: *"How did you determine that a translation was incorrect or not culturally appropriate enough?"*

The most frequently reported code was uncertainty (*n*=8). Participants described difficulty clearly determining whether a translation was culturally inaccurate, reflecting limited confidence in assessing cultural appropriateness. Unnatural wording (*n*=5) and the use of prior cultural knowledge (*n*=5) appeared with similar frequency. Some participants identified inaccuracies based on the unnatural or awkward structure of the translated sentence, while others relied on their existing cultural or background knowledge to interpret meaning distortions.

The least frequently reported code was comparison with the native language (*n*=2), with only a small number of participants explicitly referring to cross-linguistic comparison when assessing cultural appropriateness. Overall, the findings suggest that participants tended to rely primarily on intuitive judgment and perceived linguistic naturalness rather than systematic cross-linguistic comparison when identifying culturally inappropriate translations.

To understand the difficulties students face in comprehending literal and culturally accurate translations, the following question was asked: *"Was it easy for you to distinguish between a literal translation and a culturally accurate one? Please explain."* The results of the analysis are presented in Figure 3.

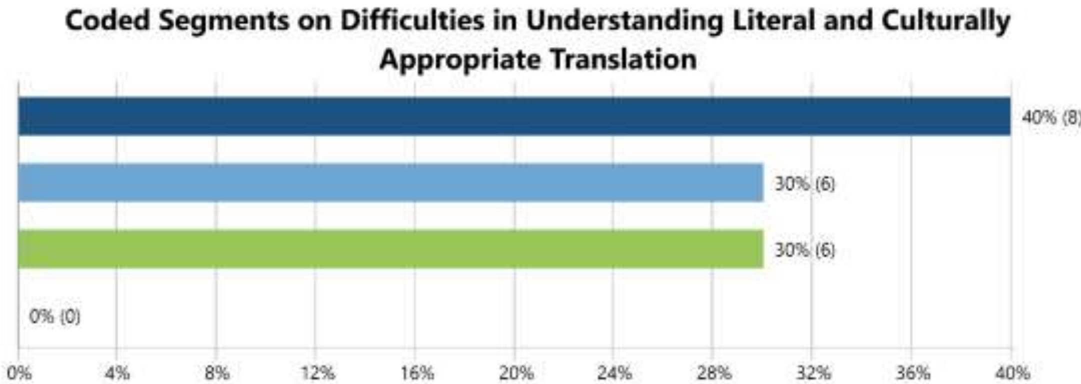


***Figure 3. Reported Difficulties in Understanding Literal and Culturally Appropriate Translation***

The figure below presents coded data segments reflecting students' reported difficulties in distinguishing between literal and culturally appropriate translations. According to the analysis, some problems tended to cluster into recurring patterns. The most common pattern concerned specific aspects of translation meaning, which more students than any others raised. In addition to the aforementioned, two other recurring patterns were observed at similar rates, suggesting that students encountered a variety of equally relevant problems. A recurring pattern, which occurred much less frequently, concerned the explicit cross-linguistic comparison, as this method was applied so rarely that it was difficult to detect any translation problems. Overall, the results reveal that intuitive judgment was used predominantly to assess the cultural relevance of the translation. Detailed student responses are presented in Table 5.

**Table 5**

*Students' Insights into the Challenges of Literal and Culturally Sensitive Translation*

| Theme | Questions | Codes | Number of codes | Participant |
|---|---|---|---|---|
| Difficulties in Understanding Literal and Culturally Appropriate Translation (*n*=20) | "Was it easy for you to distinguish between a literal translation and a culturally accurate one? Explain." (*n*=20) | Confusion | 6 | K2, K8, K10<br>E6, E8, E9 |
| | | Difficult | 6 | K5, K9<br>E1, E3, E7<br>E10 |
| | | Easy | 8 | K1, K3, K4<br>K6, K7<br>E2, E4, E5 |

*Note.* K = Kazakh-language group; E = English-language group.

Table 5 presents the main difficulties reported in translating ethnocultural units using AI. The analysis revealed three recurring patterns in students' responses: confusion during interpretation, reliance on prior cultural knowledge, and, in certain cases, perceived ease of translation.

Most students admitted experiencing confusion while understanding ethnocultural units, particularly when the AI translation did not clearly confirm the meaning. Some students were aware that cultural awareness helped them understand ethnocultural units better and thus had no problem interpreting them. On the other hand, some students reported a smooth understanding due to their familiarity with the cultural items.

The findings indicate variability in students' experiences of interpreting ethnocultural units, and this variability does not follow a clear pattern associated with any particular group of students.

**Findings for the Research Question 3: Which AI Translation Tools Do Learners Think Exhibit Better Linguistic and Cultural Adequacy?**

During the translation process, students identified which AI translation tools most effectively show linguistic and cultural adequacy. The primary goal of this question is to determine which AI translation tools best demonstrate linguistic and cultural adequacy when translating ethnocultural units. The students' answers about which AI tools are better at translating linguistic and cultural texts are shown in Figure 4.

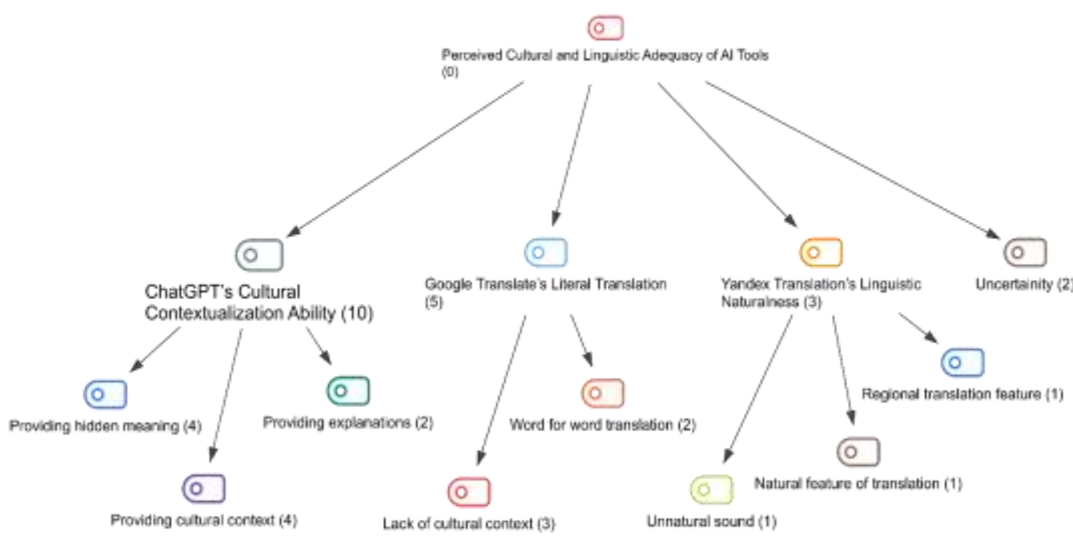


*Figure 4. Thematic Hierarchy of Students' Views on AI Systems' Cultural and Linguistic Adequacy*

Figure 4 presents the hierarchical thematic model derived from the content analysis. Within the theme of perceived cultural and linguistic appropriateness of AI-generated translations, four main categories were identified: cultural contextualization, literal translation tendencies, perceived linguistic naturalness, and uncertainty in evaluation.

As the analysis above shows, students' differing opinions were shaped by their approaches to conveying the cultural dimension of translation using AI tools. Some students mentioned a greater cultural contextualization in translations produced by some AI tools; however, others noted a lack of cultural contextualization and a tendency towards word-for-word translation. Several comments also expressed appreciation for the language aspect of the translations, even in cases where cultural loss was evident. Thus, it can be concluded that the perceived quality of AI translation is connected to interpretive diversity but not to differences among the tools. Detailed data is provided in Table 6.

**Table 6**

*Students' Evaluations of AI Translation Tools in Terms of Linguistic and Cultural Adequacy*

| Theme | Questions | Category | Code | Number of codes | Participant |
|---|---|---|---|---|---|
| Perceived Cultural and Linguistic Adequacy of AI Tools (*n*=20) | "Which of the AI tools you used seemed the most accurate in translating ethnocultural units? Why?" (*n*=20) | ChatGPT's cultural contextualization ability (*n*=10) | Providing hidden meaning | 4 | K1, K5, K7 E5 |
| | | | Providing cultural context | 4 | K3, E1, E3 E10 |
| | | | Providing explanations | 2 | K10, E7 |
| | | Google Translate's literal translation (*n*=5) | Word for word translation | 2 | K6, E2 |
| | | | Lack of cultural context | 3 | K2, E6, E9 |
| | | Yandex translation's linguistic naturalness (*n*=3) | Unnatural sound | 1 | E4 |
| | | | Natural feature of translation | 1 | K9 |
| | | | Regional translation feature | 1 | K4 |
| | | Uncertainty (*n*=2) | Uncertainty | 2 | K8, E8 |

*Note.* K = Kazakh-language group; E = English-language group.

As Table 6 shows, ChatGPT was perceived as the most appropriate tool due to its ability to provide culturally relevant translations, complete with meaning and explanations (*n*=10). Students noted that this feature enhanced comprehension of ethnocultural units. For example, one student mentioned, *"ChatGPT was the most accurate because it provided an explanation of the meaning,"* while another mentioned, *"ChatGPT produced more natural wording."*

In contrast, Google Translate was primarily associated with grammatical accuracy but limited cultural contextualization (*n*=5). Students emphasized that although translations were fast and structurally correct, cultural meanings were often missing. For example, one student noted, *"Google Translate translated faster, but without cultural context,"* while another added, *"Google is grammatically accurate, but not culturally."*

Yandex Translate was occasionally described as more natural in wording (*n*=3), particularly in rendering Kazakh language; however, inconsistencies in handling idiomatic expressions were frequently noted. One student stated, *"Yandex sounds more natural for Kazakh,"* whereas others reported that it sometimes produced unnatural or inconsistent outputs.

Overall, the findings indicate a general pattern in which students prioritized different aspects of translation quality: some emphasized cultural explanation and clarity of meaning, while others focused on grammatical or linguistic naturalness. These patterns suggest variation in how students evaluate AI-generated translations of ethnocultural units, rather than strict group-based differences.

To evaluate the perceived differences in the transmission of cultural meaning across AI-generated translations, students were asked another question: *"In your view, how do translations produced by different AI systems vary in their transmission of cultural meaning?"* The analysis focused on identifying recurring patterns in students' responses regarding variations in AI-generated translations of ethnocultural units. The main codes obtained during the analysis are presented in Figure 5 along with their frequencies.

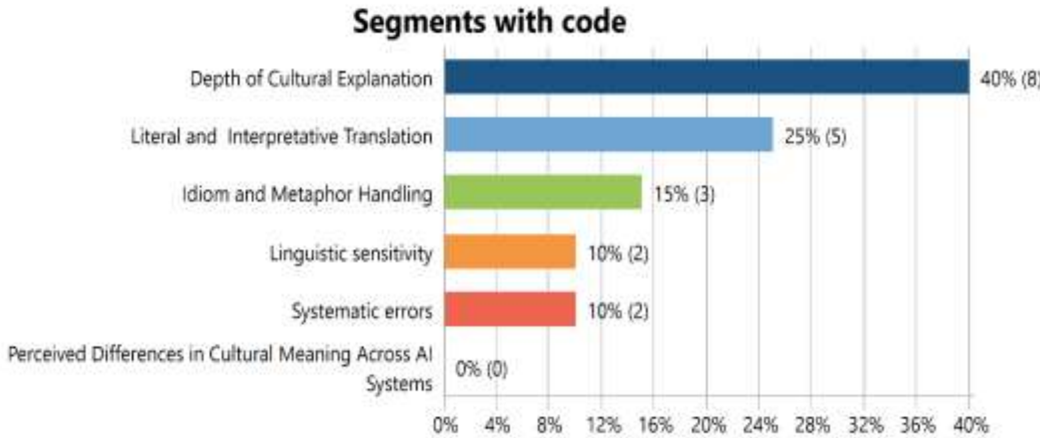


***Figure 5. Coded Segments Reflecting Perceived Differences in Cultural Meaning Across AI Systems***

As shown in Figure 5, several recurring patterns in students' perceptions of AI's transmission of cultural meaning were identified. One of the most frequently identified patterns concerned the level of interpretation of cultural meaning. The second recurring pattern involved the difference between literal and interpretive meaning generated by an AI translation. Other recurrent patterns included difficulties with the use of idioms and metaphors, awareness of linguistic form, and systematic errors in cultural representation.

All in all, the findings suggest that students see not one but several overlapping categories of variation in the cultural translations produced by AI. More detailed information on the patterns is given in Table 7.

**Table 7**

*Students' Perceptions of Differences in Cultural Meaning Across AI Systems*

| Theme | Questions | Codes | Number of codes | Participant |
|---|---|---|---|---|
| Perceived Differences in Cultural Meaning Across AI Systems (*n*=20) | "In your view, how do translations produced by different AI systems vary in their transmission of cultural meaning?" (*n*=20) | Depth of cultural explanation | 8 | K1, K2, K5 K9, K10, E1 E6, E8 |
| | | Literal and interpretative translation | 5 | K3, K6, E2 E3, E7 |
| | | Idiom and metaphor handling | 3 | K7, E5, E10 |
| | | Systematic errors | 2 | K8, E9 |
| | | Linguistic sensitivity | 2 | K4, E4 |

*Note.* K = Kazakh-language group; E = English-language group.

Table 7 reveals specific patterns in students' perceptions of variations in cultural meaning within AI-generated translations. In total, eight different codes emerged. The dominant pattern is associated with the extent of cultural explanation offered by different types of AI.

Students often noted that some types of AI offered deeper cultural explanations, whereas others relied on literal translation without providing additional cultural insight. The other significant pattern relates to literal versus interpretive translation, as some types of AI were found to provide more explanation for certain passages.

Other patterns identified through coding included the way idiom and metaphorical language were handled, the presence of systematic translation errors, and linguistic sensitivity. Therefore, the students have observed variations in cultural meaning offered by AI, including differences in the level of cultural explanation and in interpretive translation.

**Findings for the Research Question 4: How Does the Kazakh-Language Group's Engagement with AI-Translated Ethnocultural Units Affect Students' Interpretations, Correction Techniques, and Cultural Comprehension Compared to the English-Language Group?**

To explore students' strategies for checking and correcting the translation of ethnocultural units, the students were asked the following question: *"What strategies did you use to check or correct the translation of ethnocultural expressions?"* The students' responses were analyzed, and the results are presented in Figure 6.

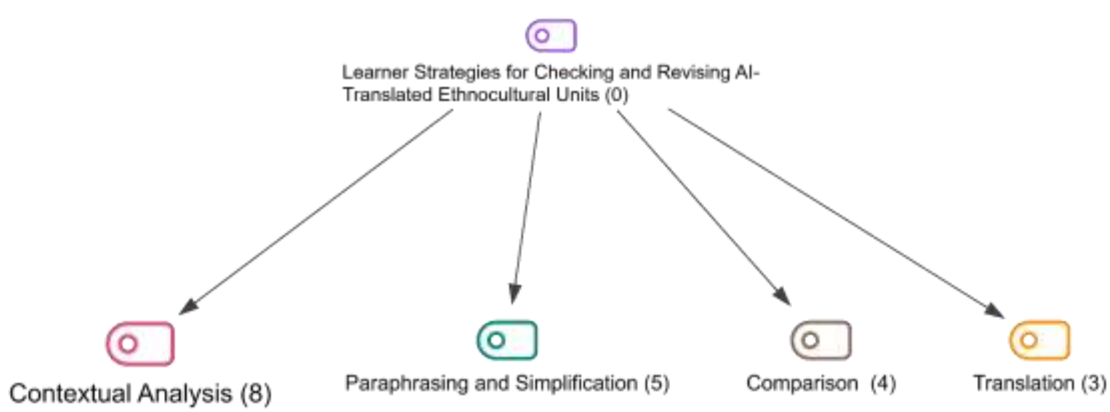


***Figure 6. Learner Strategies for Revising AI-Translated Ethnocultural Units***

The findings, illustrated in Figure 6, reveal that students used several repetitive strategies when working with AI translations of ethnocultural units. The first repetitive strategy related to contextual interpretation, whereby the meaning was tried to be understood within the sociocultural context of the phrase.

Paraphrasing and simplifying the expression to understand its meaning were other repetitive strategies used by the students. Other repetitive strategies include comparison with other translations and direct translation.

Thus, students employed various interpretive and evaluative strategies in this process. The detailed data can be found in Table 8.

**Table 8**

*Strategies Used by Students to Verify and Revise AI-Translated Ethnocultural Units*

| Theme | Questions | Codes | Number of codes | Participant |
|---|---|---|---|---|
| Strategies for verifying and revising AI-translated ethnocultural units (*n*=20) | "What strategies did you use to check or correct the translation of ethnocultural expressions?" (*n*=20) | Contextual analysis | 8 | K3, K4, K7, K8<br>E3, E4, E8, E10 |
| | | Paraphrasing and simplification | 5 | K5, K9, K10<br>E5, E9 |
| | | Comparison | 4 | K1, K2<br>E1, E7 |
| | | Translation | 3 | K6, E2, E6 |

*Note.* K = Kazakh-language group; E = English-language group.

The use of various strategies to check and correct students' AI-generated translations is outlined in Table 8. The analysis of contexts proved to be one of the strategies most frequently used by students to assess the meanings of the terms and concepts under analysis. The other strategies mentioned include paraphrasing and simplifying the meaning, comparing with other ways of expressing the same concept, and translating.

Interpretations used by the students during analysis of AI-generated translations differed in some cases. For example, some participants indicated that they preferred to reformulate meanings in their own words, while others preferred to resort to either reverse or comparison strategies of semantic verification.

To gain deeper insight into the perceptions of AI translations as an aid for ethnocultural learning, students were asked to provide answers to the following question: *"How has working with AI* *translations influenced your understanding of the ethnocultural units or concepts?"* Analysis outcomes are provided in Table 9.

**Table 9**

*Impact of AI-Mediated Translation on Students' Understanding of Ethnocultural Units*

| Theme | Questions | Codes | Number of codes | Participant |
|---|---|---|---|---|
| The impact of AI on understanding the ethnocultural units ($n$=20) | "How has working with AI translations influenced your understanding of the ethnocultural units or concepts?" ($n$=20) | Awareness of cultural distortion | 4 | K2, K5, K8<br>E3 |
| | | Uncertainty | 2 | K10, E8 |
| | | Comparative cultural thinking | 4 | K4, K6<br>E6, E7 |
| | | Critical reflection on AI | 3 | K3, E4, E10 |
| | | Increased cultural awareness | 7 | K1, K7, K9<br>E1, E2, E5, E9 |

*Note.* K = Kazakh-language group; E = English-language group.

As shown in Table 9, the patterns of students' responses to the use of AI translations in interpreting ethnocultural units were quite repetitive. They included increased focus on cultural awareness, comparative cultural cognition, and the perception of cultural distortion in AI-generated translations. Besides, some students expressed critical reflection and, at times, uncertainty during the process of interpreting ethnocultural information produced by an algorithm.

Thus, according to the findings, engaging with AI-translated ethnocultural information prompted students to reflect on the hidden cultural meanings behind certain expressions, as well as on the possibility of simplifying or partially distorting cultural meaning through AI-generated translation.

## Discussion

The findings provide essential insights into the pedagogical interpretation of AI-based tools in teaching ethnocultural units within language education. The study presents that AI-generated translation activities can facilitate students' engagement with culturally integrated expressions such as idioms, proverbs, and concepts, thereby contributing to the development of intercultural awareness and interpretive skills. Given that culture is an essential aspect of language acquisition, the study suggests that computer programs can serve as mediational tools to help learners discover cultural meanings across languages.

Recent evidence supports the use of AI tools for ethnocultural content. Tazhibayeva et al. (2026) found that AI-assisted instruction leads to better achievement and attitudes when such materials are integrated into the design. Their study shows that tools such as ChatGPT facilitate the transmission of ethnocultural knowledge at both cognitive and affective levels, aligning with the present study's findings on learners' engagement with AI-generated cultural content.

However, the findings suggest significant limitations of AI-generated translations of ethnocultural texts. The challenges associated with AI tools' inability to translate contextually, culturally, or literally indicate a mismatch between linguistic equivalence and the translation's cultural adequacy. This supports Gromann (2020), who claims that multilingual neural translation systems struggle to represent transcultural meanings because their primary function relies on correlations and lexical matching rather than cultural interpretation.

Additionally, the findings suggest that students often employ pre-existing cultural knowledge, interpretation, and comparison techniques when evaluating AI translations. Such findings highlight that human cultural consciousness remains significant in interpreting ethnocultural meanings, even when sophisticated translation mechanisms are employed. In this case, the findings affirm Messner's (2022) idea of machine inculturation, which highlights that AI mechanisms trained in a particular cultural setting may not generalize effectively across diverse sociocultural settings. Likewise, the findings affirm the arguments raised by Abhivardhan and Agarwal (2019) regarding the need for culturally conscious AI mechanisms.

The other equally important finding concerns the growing critical awareness among students of culturally produced material. During the analysis of AI outputs, students demonstrated greater attention to context, symbolism, and cultural meaning. This aligns with Espín-León et al. (2020), who claim that AI tools can recognize cultural similarities and dissimilarities through computational procedures; however, this finding implies that students themselves take an active part in this process.

Further, the findings can be used in debates regarding ICC in AI-based language learning contexts. In accordance with Byram's (1997) model of ICC, learners used interpretative competences, comparative analysis, and critical cultural awareness when considering ethnocultural units interpreted by AI. Cultural bias was observed often, while literal interpretation of messages was not accepted as the correct approach. The students used checking and comparing strategies to recover meaning. This study supports Deardorff's (2006) beliefs, suggesting that intercultural competence is gained not only through language contact but also through interpretation. These findings are also consistent with El-Shara et al. (2025), who report that university students demonstrate differences in cultural sensitivity and awareness influenced by their prior cultural knowledge and interpretive processes.

These findings are further supported by Nganga et al. (2025), who emphasize that intercultural competence develops through exposure to diverse cultural contexts and involves varying levels of ethnocentric interpretation, reflection, and cultural identity negotiation. Similarly, Akhmetova et al. (2025) show that ethnocultural concepts among Kazakh youth are shaped by generational and contextual factors, with cultural meanings being retained, modified, or lost over time. Together, these studies highlight the dynamic and context-dependent nature of intercultural competence and ethnocultural interpretation.

However, this study also raises pedagogical risks associated with the use of AI tools in the culture-learning process. For example, several participants experienced challenges when determining the cultural acceptability of the information presented, and some students tended to be strongly guided by the level of linguistic naturalness. It can lead to the creation of a phenomenon discussed by Carter (2001), called "false cultural competence," in which learners consider translations accurate in terms of their cultural aspects. Consequently, the findings emphasize the continuing importance of teacher guidance in supporting learners' critical evaluation of AI-generated cultural content.

In conclusion, the research indicates that AI translation tools have dual purposes in pedagogy. First, they can trivialize or render ethnocultural meanings culturally neutral through literal translations. Second, when introduced critically and pedagogically into language classes, they can encourage intercultural thinking and analysis. As a result, the application of AI for teaching ethnocultural languages is not enough to be technologically accessible. It should also be pedagogically based on cultural analysis and interpretation.

## Limitations and Future Research

Despite its contribution, this study has its limitations. One limitation is the sample size, which may limit the generalizability of the results. Furthermore, the analysis was based on interview data, which may indicate a subjective perspective. Future studies should increase the sample size and supplement the data with experimental tasks to objectively assess the translation's cultural appropriateness.

Based on the results obtained, several recommendations for future research will be formulated: First, future research could examine intercultural sensitivity before and after the teaching of cultural concepts using AI. Furthermore, foreign language students are encouraged to use AI translations consciously and critically, viewing them not as a final result, but as a starting point for interpreting cultural meaning. Particularly, it is useful to compare translations from multiple AI systems, analyze the differences between literal and culturally accurate translations, and verify the meaning of ethnocultural expressions through context, dictionaries, and usage examples. This strategy promotes the development of intercultural sensitivity and a deeper understanding of the cultural concepts embedded in language.

Second, it would be beneficial for teachers to incorporate tasks that focus on evaluating and debating AI translations of ethnocultural units. Students might be required, for instance, to compare translations produced by various AI tools, spot cultural errors or semantic nuance loss, and offer their own interpretations. These tasks foster critical thinking and help students recognize the limitations of automated translation systems in conveying cultural content.

Third, it is critical to include reflective assignments in the curriculum where students examine their own methods for verifying and improving AI translations. These tasks might involve making quick analytical notes about which expressions were challenging, which verification techniques worked best, and how AI tools affected their comprehension of the language's cultural nuances.

Lastly, to maintain a balance between technological support and students' growth in independent interpretive skills, instructors are urged to review and revise learning materials that use AI tools regularly. In particular, to sustain students' cognitive interest and advance their intercultural competency, assignments should progressively become more complex, incorporating increasingly intricate ethnocultural units, idioms, and culturally relevant concepts.

## Conclusion

This study aims to analyze the features of the perception, interpretation, and evaluation of ethnocultural units in texts translated using AI-based tools, taking into account strategies for assessing the translation quality of such tools and their impact on students' cultural comprehension. The study's results show that the vast majority of students in both groups can distinguish features of literal translation and recognize the loss of cultural aspects, particularly in idioms, proverbs, and phrasal verbs. Kazakh group students focused on prior knowledge and traditional experience, while English group students demonstrated strategic skills and a reliance on language structure. The comparison between the two groups indicates that generative AI-translated texts are viewed as a means of constructing cultural meaning, while traditional machine translations excel in linguistic accuracy. However, not all AI tools are considered effective for translating cultural or ethnocultural texts. This suggests that when using AI tools to translate such texts, expert involvement is essential, especially in educational contexts.

Additionally, ChatGPT is recognized as a valuable tool for providing comprehensive explanations of cultural texts, focusing on their conceptual and semantic meanings. Unlike other tools, it demonstrates an understanding of cultural nuances, especially in translations involving Kazakh ethnocultural elements. The system not only performs functional translations but also emphasizes cultural appropriateness.

During the comparative analysis of translations, strategies such as back-translation, contextual analysis, and paraphrasing were used. These strategies demonstrate that using AI tools in translation tasks contributed to the development of critical thinking and reflective skills among students simultaneously studying ethnocultural units. This demonstrates that AI plays a crucial role not only in the translation process but also as a supporting tool for developing cultural awareness and reflection in intercultural communication.

## Acknowledgments

Funding: The article was written within the framework of the research project AP26105015, *"Representation of Ethnocultural Units in the Artificial Intelligence Systems: Linguistic Aberrations and Their Systematisation,"* funded under the grant support of scientific and/or scientific-technical projects for 2025–2027 by the Science Committee of the Ministry of Science and Higher Education of the Republic of Kazakhstan.

## Conflict of Interest

The authors declare no potential conflicts of interest.

**References**

Abdujabarova, K. X. Q., & Nassiri, M. R. (2022). Main Principles of Linguocultural Concepts in Linguistics. *Oriental Renaissance: Innovative, Educational, Natural and Social Sciences, 2*(20), 163–169. DOI: 10.24412/2181-1784-2022-20-163-169

Abhivardhan, & Agarwal, R. (2019). Machine Learning and Enculturation: Perspective of International Human Rights in China. *IOSR Journal of Engineering (IOSR-JEN), 9*, 70–74. https://ssrn.com/abstract=3391858

Akhmetova, M. K., Zhanzhigitov, S.Kh., Alpysbayeva, A.Y., Sarekenova, K.K., Bibekov, K., & Abitzhanova, Z. (2025). The Representation of Ethnocultural Names in the Linguistic Consciousness of Kazakh Youth. *International Journal of Society, Culture & Language*, *13*(2), 75-87. DOI: 10.22034/ijscl.2025.2056961.3990

Anas M, M., Irawati, M., Rahayu, S., & Murti, W. (2025). Integrating Anging Mammiri Cultural Values into Learning to Improve Students' Problem-Solving Skills. *Journal of Culture and Values in Education, 8*(3), 203-236. https://doi.org/10.46303/jcve.2025.33

Bhargava, B. K., Jain, S., & Sharma, A. (2023). An ethnolinguistic research agenda for intelligent autonomous systems. In S. Jain, S. Groppe, & B. K. Bhargava (Eds.), *Semantic intelligence (Lecture Notes in Electrical Engineering, Vol. 964).* Springer. DOI: 10.1007/978-981-19-7126-6_9

Byram, M. (1997). *Teaching and Assessing Intercultural Communicative Competence*. Multilingual Matters.

Carter, R. T. (2001). Back to the Future in Cultural Competence Training. *The Counseling Psychologist, 29*(6), 787–789. DOI: 10.1177/0011000001296001

Creswell, J. W. (2009). *Research Design: Qualitative, Quantitative, and Mixed Methods Approaches* (3rd ed.). Sage.

Deardorff, D. K. (2006). Identification and Assessment of Intercultural Competence as a Student Outcome of Internationalization. *Journal of Studies in International Education, 10*(3), 241–266. DOI: 10.1177/1028315306287002

El-Shara, I. A., Hatoq, N., Alabdallat, Z., Helu, A. A., & Abu-Ghalyoun, O. (2025). Cultural Sensitivity Among University Students: Evidence from Jordan. *Journal of Culture and Values in Education, 8*(3), 115–137. DOI: 10.46303/jcve.2025.30

Espín-León, A., Jimeno-Morenilla, A., & Pertegal-Felices, M. L. (2020). Quantification of Cultural Identity Through Artificial Intelligence: A Case Study on the Waorani Amazonian Ethnicity. *Soft Computing, 24*, 11045–11057. DOI: 10.1007/s00500-019-04469-3

Felicetti, A., Himmiche, A., & Somenzi, M. (2025). Knowledge Graphs and Artificial Intelligence for the Implementation of Cognitive Heritage Digital Twins. *Applied Sciences, 15*(18), 10061. DOI: 10.3390/app151810061

Gromann, D. (2020). Neural Language Models for the Multilingual, Transcultural, and Multimodal Semantic Web. *Semantic Web: Interoperability, Usability, Applicability, 11*(1), 29–39. DOI: 10.3233/SW-190373

Hamd, M., Abdellatif, M., Ahmed, S., & Assiry, B. (2026). Promoting AI Learning Motivation for the Special English Program Students at Assiut University. *Journal of Culture and Values in Education*, *9*(2), 80-99. https://doi.org/10.46303/jcve.2026.21

Issabekova, G., Nazarbekova, A., Kudabayeva, P., Abdykadyrova, T., Rizakhojayeva, G., Kudaibergenov, A., & Akeshova, M. (2024). Teaching the Linguistic Aspects of Ethnocultural Units Employing Comparative-Historical Method. *Eurasian Journal of Applied Linguistics, 10*(3), 33–46. DOI: 10.32601/ejal.10304

Kalymova, A., Lepeshev, D., Stukalenko, N., Argimbayeva, A., & Mazhitova, S. (2026). Model of Formation of Digital Competences of Future Teachers in the Conditions of Integration of E-Learning and Artificial Intelligence Technologies. *Journal of Curriculum Studies Research*, *8*(1), 364-387. https://doi.org/10.46303/jcsr.2026.19

Kazangapova, V., Saparbaikyzy, S., Yegenissova, A. & Zhangoziyeva, M. (2024). Investigating the Relationships between Ethno-cultural Competencies, Attitudes towards Teaching National Values and General Competencies of Teacher Candidates, *Journal of Social Studies Education Research, 15*(5), 297-327. https://jsser.org/index.php/jsser/article/view/6210/717

Koyanbekova, S., Bari, A., Junussov, T., Tashimbay, S., & Ibragimova, Z. (2026). Design and Conceptual Modeling of a Synergetic Web Platform for Integrative Learning of the Kazakh Language and Expressive Stylistics. *Journal of Culture and Values in Education*, *9*(2), 162-184. https://doi.org/10.46303/jcve.2026.24

Messner, W. (2022). Improving the Cross-Cultural Functioning of Deep Artificial Neural Networks through Machine Enculturation. *International Journal of Information Management Data Insights, 2*(2), 100118. DOI: 10.1016/j.jjimei.2022.100118

Miles, M. B., & Huberman, A. M. (1994). *Qualitative Data Analysis: An Expanded Sourcebook* (2nd ed.). Sage.

Mitsa, O., Sharkan, V., Maksymchuk, V., Varha, S., & Shkurko, H. (2023). Ethnocultural, educational, and scientific potential of the interactive dialects map. In *2023 IEEE International Conference on Smart Information Systems and Technologies (SIST)* (pp. 226–231). IEEE. DOI: 10.1109/SIST58284.2023.10223544

Mitsa, O., Voloshchuk, Y., Levchuk, O., & Petsko, V. (2025). A comparative study of machine learning algorithms and the prompting approach using GPT-3.5 Turbo for text categorization. In Z. Hu, F. Yanovsky, I. Dychka, & M. He (Eds.), *Advances in computer science for engineering and education VII. ICCSEEA 2024* (Lecture Notes on Data Engineering and Communications Technologies, Vol. 242). Springer. DOI: 10.1007/978-3-031-84228-3_13

Nganga, L., Kambutu, J., Akpovo, S. M., & Thapa, S. (2025). Promoting Intercultural Competence: Experiences from Kenya and Nepal Study Abroad. *Journal of Social Studies Education Research, 16*(4), 1–27. https://jsser.org/index.php/jsser/article/view/6279/752

Norton, B. (2013). Identity, literacy, and the multilingual classroom. In S. May (Ed.), The multilingual turn: Implications for SLA, TESOL, and bilingual education (1st ed., pp. 103–122). Routledge. DOI: 10.4324/9780203113493

Saldaña, J. (2021). *The Coding Manual for Qualitative Researchers* (4th ed.). Sage Publications.

Sobkowiak, P. (2019). The Impact of Studying Abroad on Students' Intercultural Competence: An Interview Study. *Studies in Second Language Learning and Teaching, 9*(4), 681–710. DOI: 10.14746/ssllt.2019.9.4.6

Tazhibayeva, S., Kanatkerey, A., Mamayeva, G., Kemerbay, R., Beisenuly, Z., & Buribayeva, M. (2026). The Impact of Artificial Intelligence Applications on Linguistic and Literary Connections among Turkic Peoples Based on Ethnocultural Codes. *Journal of Ethnic and Cultural Studies, 13*(3), 207–228. https://www.jstor.org/stable/48877695

Ternavskaya, M. M., & Bogdanova, Y. V. (2023). Ethnocultural Identity in Literary Text. *Keruen, 78*(1), 160-173. DOI: 10.53871/2078-8134.2023.1-15

Trede, F., Bowles, W., & Bridges, D. (2013). Developing Intercultural Competence and Global Citizenship through International Experiences: Academics' Perceptions. *Intercultural Education, 24*(5), 442–455. DOI: 10.1080/14675986.2013.825578

Vedaschi Ozzola, M. (2025). The Role of Forums in Enhancing Vocabulary Acquisition in English as Foreign Language Classrooms. *Research in Social Sciences and Technology, 10*(3), 145-159. https://doi.org/10.46303/ressat.2025.46

Vossen, P. (1998). Introduction to EuroWordNet. In P. Vossen (Ed.), EuroWordNet: A multilingual database with lexical semantic networks. Springer. DOI: 10.1007/978-94-017-1491-4_1

Wolff, F., & Borzikowsky, C. (2018). Intercultural Competence by International Experiences? An Investigation of the Impact of Educational Stays Abroad on Intercultural Competence and its Facets. *Journal of Cross-Cultural Psychology, 49*(3), 488–514. DOI: 10.1177/0022022118754721

Zhunussova, S., Baimanova, L., & Naviy, L. (2026). Development of Soft Skills in Pre-Service Foreign Language Teachers: A Structural-Functional Model. *Journal of Culture and Values in Education*, *9*(2), 268-291. https://doi.org/10.46303/jcve.2026.29