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GENDER BIAS IN ENGLISH–UZBEK MACHINE TRANSLATION: A COMPARATIVE STUDY OF AI AND HUMAN OUTPUTS

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ANNOTATION

This article investigates gender bias in English-Uzbek machine translation systems by comparing AI-generated translations with human translator outputs. The study highlights how AI models often reproduce or exaggerate gender stereotypes embedded in English datasets, while human translators rely on contextual reasoning and cultural adaptation to mitigate bias.

Keywords: *Gender bias, machine translation, Uzbek language, AI vs human translation, neural MT, stereotypes, bilingual communication.*

АННОТАЦИЯ

В данной статье исследуется гендерная предвзятость в англо-узбекских системах машинного перевода путем сравнения переводов, созданных искусственным интеллектом, с переводами, выполненными человеком. В исследовании подчеркивается, что ИИ-модели нередко воспроизводят или усиливают гендерные стереотипы, присутствующие в английских датасетах, тогда как человеческие переводчики опираются на контекстуальное мышление и культурную адаптацию, чтобы смягчить предвзятость.

Ключевые слова: *гендерная предвзятость; машинный перевод; узбекский язык; перевод ИИ и человека; нейронные системы МП; стереотипы; билингвальная коммуникация.*

ANNOTATSIYA

Ushbu maqola ingliz-o‘zbek mashina tarjimasi tizimlaridagi gender tarafkashlikni AI tomonidan yaratilgan tarjimalar va inson tarjimonlari bajargan tarjimalar orqali tahlil qiladi. AI modellarining ko‘pincha gender stereotiplarini takrorlashi yoki kuchaytirishi, inson tarjimonlarining esa kontekst orqali tarafkashlikni yumshatishga intilishi ko‘rib chiqiladi.

Kalit so‘zlar: *Gender tarafkashlik, mashina tarjimasi, o‘zbek tili, AI va inson tarjimasi, neyron MT, stereotiplar, ikki tilli kommunikatsiya.*

Introduction.

Machine translation (MT) is rapidly reshaping how English-Uzbek bilingual communication unfolds in everyday life from students writing essays to professionals handling international correspondence. Its speed and convenience mean that thousands of users now rely on MT systems as an invisible linguistic assistant. However, beneath this efficiency lies an emerging sociolinguistic issue: the subtle but persistent reproduct.[1]

One of the core challenges stems from the structural differences between English and Uzbek. English pronouns such as *they* or occupa*te* are inherited *“The nurse said they would co* is of *“The engineer explained the problem”*.

This pattern does not emerge from malice but from data. MT systems learn from massive text corpora, and if those texts reflect traditional gender roles, the systems reproduce them. Yet, for real people using these tools, the consequences can feel personal. Students may feel their writing is subtly altered in ways that misrepresent their intent. Educators might notice that translations reinforce outdated gender expectations. In everyday messaging, a gender-neutral statement can become unintentionally biased, creating misunderstandings or disco.[2]

[1] Berdikulov, S. (2017). *Issues of gender representation in Uzbek linguistic culture*. Uzbek Linguistic Journal, 4, 22–30.

[2] Bolukbasi, T. et al. (2016). Man is to Computer Programmer as Woman is to Homemaker?

Moreover, the issue becomes more important as MT is increasingly integrated into public services, educational platforms, and workplace communication. When an automated system consistently assigns men to positions of authority and women to caregiving roles, it shapes perceptions especially for younger users who trust digital tools. The translation is no longer just linguistic; it becomes ideologic.[1]

But there is also a human side to this challenge. Many bilingual users begin to notice these biases and actively correct them. Teachers discuss them with students, translators adapt strategies to counteract stereotypes, and ordinary users develop a habit of checking MT outputs more critically. In this sense, MT bias becomes a shared learning moment: a reminder that technology does not simply reflect language, but also the society from which that language emerges.

Ultimately, addressing gender bias in English–Uzbek MT is not only a technical task it is a cultural responsibility. Developers, educators, and users can work together to create translations that respect linguistic neutrality and human dignity. As machine translation continues to evolve, so too must our awareness of the values we allow it to encode.

Literature review.

Gender bias in translation is not an isolated technical flaw it is a reflection of the deeper linguistic and cultural layers that shape how societies perceive gender. When English-Uzbek texts are translated, especially by machine translation systems, three intertwined mechanisms often come into play: lexical stereotypes, grammatical assumptions, and socio-cultural expectations.

Lexical stereotypes emerge when certain professions or roles are habitually associated with one gender. For example, words like *nurse*, *teacher*, or *secretary* tend to be interpreted as feminine, while *engineer*, *manager*, or *scientist* are often rendered as masculine. These associations may not be explicitly encoded in English, but Uzbek translations frequently activate them. As a result, a gender-neutral English sentence

[1] Crystal, D. (2011). Internet Linguistics.

becomes gender-marked in Uzbek simply because the system fills in what it "expects" rather than what the author intended.[1]

Grammatical assumptions also contribute to bias. Although Uzbek does not grammatically require gendered pronouns, translators both human and machine often feel compelled to choose one, especially in narrative contexts. English structures that rely on neutral pronouns such as *they* or omit gender altogether can be challenging: MT models tend to resolve ambiguity by selecting the statistically most common gender found in their training data. [2]Thus, ambiguity, which is a natural part of human language, is transformed into certainty but often the wrong kind of certainty.

Socio-cultural expectations add a deeper layer to this process. Cultures shape language, and languages reinforce cultural norms. If the training corpora contain texts where men dominate public, technical, and leadership domains, while women appear in domestic or caregiving roles, neural MT models will encode these patterns as "default realities". The result is translations that subtly reproduce traditional gender hierarchies even when the source text is neutral or intentionally inclusive.

Neural MT systems do not invent these biases; they inherit them. Their algorithms learn by identifying statistical associations across millions of sentences. If the data skews toward stereotyped representations, the model internalizes these biases as reliable patterns. In this way, gender bias is not merely an error but a predictable output of the system's training environment.[3]

Yet, recognizing this problem has a human implication. Users begin to notice when translations do not reflect their meaning. Educators and linguists advocate for more diverse, balanced corpora. Developers experiment with debiasing techniques. Each of these efforts acknowledges a simple truth: translation is not just the transfer of words it is the transfer of social values.

[1] Ergasheva, M. (2022). *Gender and cultural nuance in Uzbek translation practices.* International Journal of Linguistics and Translation Studies, 5(2), 44–57.

[2] Holmes, J., & Meyerhoff, M. (Eds.). (2020). *The handbook of language and gender*. Wiley.

[3] Hovy, D. & Spruit, S. (2016). Gender Bias in NLP.

By addressing gender bias in MT, we are not only improving linguistic accuracy; we are participating in a broader cultural shift toward fairness and representation in digital communication.

Research methodology.

To understand how gender bias manifests in real English-Uzbek translation practice, a dataset of 200 carefully selected English sentences was tested across several major MT platforms Google Translate, DeepL, ChatGPT-based MT engines, and a number of regional translation tools commonly used in Central Asia. These systems were chosen because they represent the tools that ordinary users, students, educators, and professionals most frequently rely on in their daily communication.

The test set included a mix of gender-neutral sentences, ambiguous structures, and context-rich examples involving professions and personal roles. By exposing each system to the same linguistic challenges, it became possible to observe how consistently (or inconsistently) different tools handled gender assignment.

To provide a meaningful benchmark, these machine-generated translations were then compared with outputs produced by experienced professional human translators. These translators were instructed to preserve neutrality unless the context explicitly required specifying gender a practice aligned with modern translation ethics. Their work served as the “gold standard” against which MT errors, biases, and interpretative leaps could be evaluated.

The comparison revealed not only the accuracy gaps but also the subtle choices each system made when confronted with uncertainty. Some MT tools defaulted to male referents for roles associated with leadership or technical expertise, while others tended to feminize caregiving and service-oriented professions. Human translators, in contrast, approached these sentences with careful consideration of pragmatic meaning, cultural nuance, and the author’s likely intention.

This evaluation process underscores an important point: machine translation does not simply convert text it reveals the assumptions embedded in its training data. By

comparing MT output with human judgment, we begin to see where technology aligns with human reasoning and where it drifts into stereotype-driven interpretation.[1]

Analysis and results.

The comparative analysis revealed a clear pattern: AI-based translation systems disproportionately rely on masculine defaults, especially when processing sentences related to professional or high-status occupations. Roles such as *engineer*, *manager*, *researcher*, *lawyer*, or *director* were almost automatically rendered with masculine subjects in Uzbek, even when the original English text contained no gender indicators. This tendency reflects the statistical imprint of training corpora in which men appear more frequently in technical, leadership, or public-facing domains.

In contrast, when the input sentences involved emotional situations, care-related responsibilities, or family roles such as *nurse*, *assistant*, *teacher*, *caregiver*, or *parenting scenarios* several MT systems displayed an opposite but equally stereotypical pattern: they defaulted to feminine interpretations. In emotional contexts, AI often amplified traditional assumptions, for instance translating neutral statements about comforting, helping, or expressing feelings with “u ayol” or other markers that implicitly signal femininity. Such choices do not arise from linguistic necessity but from the cultural biases encoded in the data that trains these models.

Overall, the findings illustrate that AI does not merely translate text it unintentionally reproduces and magnifies existing societal biases, unless deliberately corrected. Humans, meanwhile, operate with an awareness of nuance, responsibility, and context, making their translations more inclusive and culturally balanced.

AI tends to exaggerate Western gender stereotypes, struggle with pronoun ambiguity, and misinterpret Uzbek kinship norms. Human translations show stronger contextual understanding and bias mitigation.

Conclusion.

[1] Mirzayeva, D. (2020). *Translation ambiguity in Uzbek: A socio-linguistic perspective.* Journal of Central Asian Languages, 8(1), 15–34.

The study concludes that addressing gender bias in English–Uzbek machine translation requires more than incremental technical adjustments it calls for a deeper rethinking of how AI systems are trained and deployed. A central finding is that current MT models lack sufficient Uzbek-specific training data, especially high-quality corpora that represent modern, inclusive language use. Most large-scale models rely heavily on multilingual datasets dominated by English and other global languages, leaving Uzbek underrepresented and culturally flattened. Without richer, more diverse Uzbek input, models continue to fill gaps with biased assumptions learned from unrelated linguistic contexts.

Finally, the study highlights the promise of hybrid human-AI workflows. When AI handles initial drafts and humans perform targeted editing especially in context-sensitive areas like gender the result is both efficient and ethically responsible. Human oversight can catch biases that algorithms overlook, while AI can accelerate routine tasks, allowing translators to focus on nuance. This synergy ensures that technological speed does not come at the expense of cultural sensitivity or social equity.

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