

B. Sc. Information Systems

Berlin School of Economics and Law

Department 1: Business and Economics

Bachelor's Thesis

**Detecting Gender Bias in  
English-German Translations  
using Natural Language Processing**

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## **Abstract**

Recent years have seen extensive research on bias in MT. A systematic review of the literature by Shrestha and Das offers a thorough overview of this issue, detailing its scope, impact, and key findings relevant to my thesis. Several case studies comparing English to both grammatical-gender languages (e.g., Spanish, Italian) and non-gender-marking languages (e.g., Hungarian) consistently identify biases, including the assignment of stereotypical gender roles and a default tendency to use male pronouns Stanovsky et al. (2019); Prates et al. (2019); Smacchia et al. (2024). The methodologies used in these studies will be valuable for my own implementation. Lastly, the study by Lardelli et al. on the challenges of translating English into German lays the foundation for my analysis. It provides data for testing the translation of gender-neutral terms in context, as well as a gender-fair German dictionary, both of which I can build upon.

## Sperrvermerk

Die vorgelegte Masterarbeit basiert auf internen, vertraulichen Daten und Informationen des Unternehmens ..... In diese Arbeit dürfen Dritte, mit Ausnahme der Gutachter und befugten Mitgliedern des Prüfungsausschusses ohne ausdrückliche Zustimmung des Unternehmens und des Verfassers keine Einsicht nehmen. Von diesem Verbot ausgenommen sind außerdem jene Personen, die auch ansonsten zur Einsichtnahme in die genannten Daten und Informationen befugt sind. Eine Vervielfältigung und Veröffentlichung der Masterarbeit ohne ausdrückliche Genehmigung – auch auszugsweise – ist nicht erlaubt.

Berlin, den 01. Januar 2099

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# Contents

<b>List of Figures</b>	<b>v</b>
<b>List of Tables</b>	<b>vi</b>
<b>1 Introduction</b>	<b>1</b>
1.1 Motivation . . . . .	2
1.2 Problem Statement and Research Questions . . . . .	3
1.3 Scope and Limitations . . . . .	4
1.4 Overview of Chapters . . . . .	4
<b>2 Related Work</b>	<b>5</b>
2.1 Literature Search Process . . . . .	5
2.2 Foundations of Gender Bias in Natural Language Processing . . . . .	7
2.3 Sources and Manifestations of Bias . . . . .	8
2.4 Linguistic Challenges in English-German Translation . . . . .	8
2.5 Mitigation Strategies and Current Limitations . . . . .	9
2.6 Positioning of My Work . . . . .	10
<b>3 Conceptual Frameowrk</b>	<b>11</b>
3.1 What type of gender bias will i refer to and why . . . . .	11
3.2 What is Machine Bias? . . . . .	11
3.3 Binary Classification in NLP . . . . .	11
3.4 Pre-trained Language Model: BERT . . . . .	11
<b>Bibliography</b>	<b>12</b>

## List of Figures

1	Google Translate assigns stereotypical genders to occupational roles. . . . .	16
2	DeepL shows a similar bias in the same sentence, highlighting consistent patterns across MT tools. . . . .	16
3	Gender-specific translation by Google Translate for ambiguous pronouns. .	16

## List of Tables

2.1	Key concepts relevant to this thesis . . . . .	6
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# 1 Introduction

Machine Translation (MT) is a sub-field of computational linguistic that uses computer software to translate texts between languages (Lin and Chien 2009). It is a major area within Natural Language Processing (NLP), a branch of Artificial Intelligence (AI) (Smacchia et al. 2024). This technology helps millions of people communicate across languages, whether in everyday situations or high-stakes domains like healthcare, law and business (Kappl 2025). It can be used to translate everything from casual conversations to medical prescriptions and legal documents, with tools like Google Translate serving over 200 million users daily (Prates et al. 2019; Shrestha and Das 2022). According to a market analysis by SkyQuest (2025), the MT market size was valued at 980 million USD in 2023 and is projected to reach 2.78 billion USD by 2023, with new advanced translation models appearing on the market frequently.

With this growing availability and accessibility of free MT tools capable of handling complex sentences, their use in translating large volumes of content is increasing (Thompson et al. 2024). This not only expands their influence on global access to information, but also shapes how readers perceive and interpret that content. Automated and unsupervised translations raise new concerns: not just about quality, but also about bias. One aspect is gender bias. Several studies (Smacchia et al. 2024; Cho et al. 2019; Stanczak and Augenstein 2021; Soundararajan and Delany 2024) confirm that MT systems trained on large-scale datasets that incorporate societal biases, can learn and perpetuate gender biases present in the training data. In short, if the training data reflects gender stereotypes, the translation system is likely to repeat them. This includes, but is not limited to, the insertion of gendered pronouns in place of originally gender-neutral terms, and the use of stereotypically gendered occupational titles.

There is a risk of incorrect gender assignment when translating between languages with and without grammatical gender. For example, the gender-neutral English sentences "The surgeon is hard-working" and "The nurse is hard-working" are translated into German as "Der Chirurg ist fleißig" and "Die Krankenschwester ist fleißig" respectively, as seen in Figure 1 and Figure 2. These translations introduce occupational gender stereotypes. "Der Chirurg" is the masculine form of "surgeon" in German, adding a male gender where the

original English sentence did not specify one. Similarly, “Die Krankenschwester” is the feminine form of “nurse,” again assigning a gender that was not present in the source. These patterns are not just technical flaws. They can reinforce harmful stereotypes in real-world contexts. The following section outlines the broader motivation behind this thesis.

### 1.1 Motivation

#### 1.1.1 Social and Ethical Importance of Addressing Gender Bias

Academia has come to the consensus that MT systems do default to male pronouns when gender in the source sentence is ambiguous. In addition, as shown in the earlier example where "the surgeon" and "the nurse" were translated with stereotypical genders, the reinforcement of occupational stereotypes is an increasing concern. When MT is used for job descriptions, recommendation letters, or resumes and it inserts or reinforces unfairly gendered language (Bolukbasi et al. 2016), it may discourage individuals whose gender is misrepresented or stereotyped. In turn, this would reduce their chances of success in recruitment processes. Failing to address this issue can bring broader consequences for business, leading to the exclusion of qualified candidates, reduce diversity and contradict international standards. Organizations like the United Nations, UNESCO, and the European Union stress the importance of gender equality and inclusive language, making gender equality one of the 17 Sustainable Development Goals for 2030 (Sczesny et al. 2016; United Nations 2023). Moreover, language influences how people think. There have been consistent findings that speakers do not understand masculine forms as referring to both genders equally, but interpret them in a male based way (Sczesny et al. 2016). Gender-fair language is more commonly used in official texts, much less in private messages. Still, exposure matters. The more often people see inclusive forms, the more normal they become. Promoting awareness of these patterns is an important step toward reducing bias in society.

#### 1.1.2 Why Detection Systems Are Needed

Current research on this topic tends to focus more on the quantitative measurement of gender bias (Rescigno and Monti 2023; Barclay and Sami 2024; Smacchia et al. 2024), e.g. counting the occurrences of gendered pronouns or grammatical forms in outputs when prompting models with a neutral input. It is then often compared against a standard or desired outcome like real-world demographic distributions (Smacchia et al. 2024; Prates et al. 2019) or human evaluation (Lardelli et al. 2024; Savoldi et al. 2024). However, at



this stage, evaluations are not enough for accountability. Few approaches address an active gender bias detection layer. While this gap remains in translation systems, similar issues have been addressed in other domains. For example, as summarized by Shrestha and Das (2022), Schwemmer et al. (2020) propose a detection framework to uncover gender bias in facial recognition technologies. Their findings show that these systems are more accurate in identifying individuals as women when the images conform to stereotypical feminine features like long hair or makeup. In some cases, systems even associated such images with stereotypically gendered labels like "kitchen" or "cake," despite these elements not being present. A detection system specifically for MT would increase linguistic transparency, because without the development of bias-aware tools, problematic translations are likely to scale without oversight. Therefore, addressing gender bias in MT becomes both a social and ethical necessity.

### 1.2 Problem Statement and Research Questions

The core problem boils down to the significant bias towards the masculine form in English-German MTs, sometimes constituting 93-96% of translations for isolated words (Lardelli et al. 2024). These outputs often reflect social stereotypes rather than objective translations, yet current systems offer no mechanism to detect or signal when such bias occurs (Rescigno and Monti 2023). To address this, this thesis deploys a blackbox approach to explore how fine-tuning a pre-trained multilingual BERT model can help detect gender bias in MT outputs. The model takes an input sentence and its corresponding German translation and predicts whether the translation introduces gender bias. It focuses on identifying two common cases: added gendered pronouns and wrongly gendered nouns.

The translation system used is Opus-MT, an open-source neural MT model. Translations are passed through BERT, trained on a dataset I have constructed by combining and adapting several existing datasets from other researchers. The classifier is lightweight and efficient, aiming for transparent behavior and easy integration into other tools (Devlin et al. 2019). Its predictions are used to highlight biased parts in a web-based demo. The goal is not to build a perfect detector, but a working proof of concept that shows how bias can be flagged automatically. This supports more critical use of MT systems and encourages further development of bias-aware translation tools.

The main research question is: **"How can a NLP-based binary classification model detect gender bias in English-German translations?"**. This involves building a suitable training dataset, selecting features that capture bias patterns, and evaluating how

well the model generalizes across different domains.

### 1.3 Scope and Limitations

This thesis focuses only on English-to-German machine translation due to my fluency in both languages, allowing me to evaluate the outputs and datasets directly. Extending the work to other language pairs would require native-level understanding to reliably identify subtle gender patterns and translation errors, which is beyond the current scope. More generally, gender bias in language is a complex issue altogether that goes far beyond simple word associations. It becomes especially difficult to detect when sentences contain multiple subjects, indirect references, or ambiguous pronouns. For example, as Barclay and Sami (2024) explain, the sentence “He went to see her mother” clearly implies three people, while “He went to see his mother” could refer to either two or three. These types of structures introduce ambiguity that makes annotation and evaluation much harder. Creating a dataset that captures such linguistic complexity would require significant effort and careful control of variables. One broader limitation in building datasets for complex scenarios with multiple subjects is the difficulty of isolating the influence of each gendered entity (Lardelli et al. 2024). When working with natural language sources, it becomes hard to tell what caused the bias in the translation. Because of this, the focus of this thesis is on simpler sentence structures with a single subject. This makes it easier to identify and explain bias patterns. It also fits the intended use case: translating business texts like job advertisements or reports, which rarely involve multiple nested clauses or ambiguous pronouns.

### 1.4 Overview of Chapters

## 2 Related Work

This section outlines key findings of related work on gender bias in MT, with a focus on the English-German language pair to build the theoretical knowledge base. The research aims are to (1) define the core concept of gender bias in MT, (2) establish the relevance of the topic, (3) identify the research gap, and (4) justify technical design choices. To support this, I examine datasets, model types, and tools used in previous studies.

For the literature review I combined incremental and conceptual literature review methods, where each source led to the identification of the next. Based on this progression, I identified key concepts and used them to organize and interpret the literature, aligning with a conceptual approach. The structure followed the qualitative Information Systems framework by Schryen (2015) and was further informed by Shrestha and Das (2022) and Savoldi et al. (2025), who both conducted systematic reviews on gender bias in ML and MT respectively.

### 2.1 Literature Search Process

#### 2.1.1 Search Sources and Tools

Sources were primarily searched on Google Scholar and Perplexity, which served as an additional search engine. Prompts and outputs from Perplexity have been saved and are included in the appendix. To organize and manage the collected sources, Zotero was used throughout the process.

#### 2.1.2 Literature Review Framing

To answer the four research aims, I have defined the key concepts in Table 2.1. Key search terms consisted of *gender bias*, *machine translation*, *AI*, *machine learning*, *German*, *stereotypes*, and *detection*. The focus was on literature published between 2019 and 2025 to maintain relevance and currency, while foundational and definitional works from earlier periods were selectively included. The initial search for the term *gender bias in machine translation* returned over 18,000 results. Through my iterative selection process, this was narrowed down to 34 core sources.

Key Concept	Description
Stereotypes and Biases in Society	Introduces the social foundations of bias by explaining how stereotypes form, persist, and shape expectations about gender roles. Necessary to understand why certain translation outputs may reflect or reinforce societal gender norms.
Machine and Algorithmic Bias	Explains how social biases can enter ML systems through data, design choices, or feedback mechanisms. Sets the groundwork for understanding how gender bias can emerge in translation models used in this thesis.
Gender Bias in English-German Translation	Focuses on the specific challenges of translating between English and German, where the lack of grammatical gender in English and its necessity in German can cause biased outputs. Defines the types of gender bias relevant to the classification task in this thesis.
Bias Detection Frameworks	Reviews existing methods for identifying gender bias in language data and ML outputs. Helps justify the choice of a classification approach for detecting bias in translations.

Table 2.1: Key concepts relevant to this thesis

### 2.1.3 Citation Tracking

Backward citation searching involved reviewing references cited by selected papers, prioritizing frequently cited and foundational works relevant to gender bias in MT. Forward citation searching used Google Scholar’s “cited by” function to identify newer research citing those key papers. Filtering with specific terms (e.g., *German* and *machine translation*) was applied during forward search to maintain focus. In addition to the main review process, supplementary sources were included as needed throughout the writing phase. These consist of contextual references, statistics, or secondary citations that support specific points but were not part of the core conceptual or methodological framework.

### 2.1.4 Selection Criteria and Screening Process

Titles and abstracts were manually screened to select relevant studies. Inclusion criteria required sources to specifically address gender bias in MT, provide examples or discussions of gender-related errors, or explain the significance of gender bias in this context. Exclusion criteria filtered out studies focusing on general NLP bias without a direct link to MT, non-gender biases without clear gender connection, and highly technical papers lacking contribution to the general understanding of gender bias. Full texts were reviewed after initial screening to confirm relevance and extract insights. Redundant sources not providing new perspectives aligned with the thesis goals were excluded.

## 2.2 Foundations of Gender Bias in Natural Language Processing

### 2.2.1 Empirical Evidence

**Foundational studies:** The existence of gender bias in MT is well-documented. First mentions of this issue date back to over a decade ago, having been recognized by a paper by Schiebinger in 2014. Since then, there has been a general increase in research papers focusing on this topic, especially between 2019 and 2023 (Savoldi et al. 2025).

Prates et al. (2019) conducted a large-scale quantitative study using Google Translate, translating sentences such as "He/She is an engineer" from twelve gender-neutral languages into English. The study revealed a significant overrepresentation of male pronouns, particularly in STEM-related occupations. This skew was not attributable to actual gender distributions in the labor market, suggesting that the bias stemmed from imbalances in the system's training data. The paper received widespread media coverage, which was followed by a policy change by Google to present both feminine and masculine official translations for ambiguous queries (Google 2018), acknowledging that their model inadvertently replicated gender biases (refer to Figure 3).

Stanovsky et al. (2019) introduced WinoMT, a challenge set designed to evaluate gender bias in translations of English sentences into eight target languages with grammatical gender. The study showed that both commercial and academic MT systems failed to preserve correct gender in non-stereotypical roles, while performing better on stereotypical ones. In line with the findings of Prates et al., the study demonstrated a systematic preference for traditional gender roles in translations. This pattern is further supported by Cho et al. (2019), who showed that occupational terms exhibit higher levels of gender bias across systems compared to other semantic categories.

These foundational studies not only confirm the existence of systematic gender bias in MT outputs, but also lay the groundwork for subsequent research that builds upon their findings to develop more robust evaluation methods and mitigation strategies.

**Human-Centered Studies:** In addition to analyzing MT outputs directly, some studies have assessed the real-world implications of gender bias by measuring its impact on human effort. Savoldi et al. (2024) conducted a human-centered evaluation in which approximately 90 participants were tasked with post-editing MT outputs to ensure gender-accurate translations.

The study employed behavioral metrics such as time to edit and the number of edits, measured through human-targeted error rate, to quantify the effort required. The results showed that post-editing feminine translations required nearly twice as much time and four times the number of editing operations compared to masculine counterparts. Consequently this effort gap also translates into higher economic costs, suggesting a measurable quality-of-service disadvantage that disproportionately affects women. Savoldi et al. concluded that current automatic bias metrics do not sufficiently capture these human-centered disparities, emphasizing the need for evaluation methods that reflect real user experience.

### 2.2.2 Types of Gender Bias

### 2.2.3 Implications

## 2.3 Sources and Manifestations of Bias

### 2.3.1 Causes of Gender Bias

## 2.4 Linguistic Challenges in English-German Translation

### 2.4.1 Grammatical Gender

Although both English and German originate from the Indo-European language family (Baldi 2008), they have different characteristics. English does not assign grammatical gender to nouns. The article "the" is used universally, independent of what it refers to. On the contrary, German assigns one of three grammatical gendered articles to objects: "der" (m), "die" (f) and "das" (n). The form or ending of a noun may also change depending on its grammatical gender. While English has a few gendered word pairs, such as "actor" (male) and "actress" (female), gender distinctions in German apply broadly across the entire noun system. "Der Student" refers to a male student, whereas "die Studentin" refers to a female student.

### 2.4.2 Gender-Fair Language

The English sentence "The students are studying" does not indicate the genders of the individuals involved. There are various ways to translate that sentence into German. The plural forms of the gendered term "student" would be "die Studenten" (multiple male students) and "die Studentinnen" (multiple female students). The problem arises when there is a mix of male and female students or when the genders are unknown. There are four main approaches to gender-fair language (GFL) identified by Lardelli et al. (2024). I will not discuss two of them further because they are less common and face greater hurdles for broader public and professional acceptance.

#### Gender-neutral rewording

This uses neutral terms instead of gendered nouns, e.g. "Die Studierenden lernen". A challenge for this version is that neutral alternatives do not exist for every noun and can therefore not be consistently applied.

#### Gender-inclusive characters

This combines masculine and feminine forms using a character like "", " " or "\_", e.g. "Die Student\*innen lernen". This method is consistent, however it may interrupt the reading flow and there is a lack of standardization.

#### The Generic Masculine

In both singular and plural contexts, there is a phenomenon known as the *generic masculine* (GM), referring to the default use of the masculine grammatical gender. The example sentence would translate to "Die Studenten lernen", using just the male form to refer to a (potential) mix of genders. The GM is supposed to be gender-neutral, but studies indicate that these forms are semantically much closer to explicitly masculine forms (Schmitz 2022). Similarly, Rescigno and Monti (2023) observed a predominance of masculine forms in translation outputs (approximately 90% in Google Translate and 85–88% in DeepL—for) English–Italian and English–German pairs, even when the original sentences contained relatively few masculine references.

## 2.5 Mitigation Strategies and Current Limitations

Technical Approaches:

## 2 *Related Work*

Fine-tuning models with balanced data 9

Context-aware architectures 11

Gender-neutral translation strategies 9

LLM Potential: While promising, current LLMs like ChatGPT often introduce new biases when explicitly prompted for gender alternatives 9.

Persistent Challenges:

English-centric approaches dominating research 4

Disconnect between translation technologies and operational contexts 4

Difficulty handling non-binary identities

### **2.6 Positioning of My Work**



### 3 Conceptual Frameowrk

3.1 What type of gender bias will i refer to and why

3.2 What is Machine Bias?

3.3 Binary Classification in NLP

3.4 Pre-trained Language Model: BERT

## Bibliography

- Baldi, P. (2008). English as an Indo-European Language. In Momma, H. and Matto, M., editors, *A Companion to the History of the English Language*, pages 127–141. Wiley, 1 edition.
- Barclay, P. J. and Sami, A. (2024). Investigating Markers and Drivers of Gender Bias in Machine Translations.
- Bolukbasi, T., Chang, K.-W., Zou, J., Saligrama, V., and Kalai, A. (2016). Man is to Computer Programmer as Woman is to Homemaker? Debiasing Word Embeddings. *NIPS’16: Proceedings of the 30th International Conference on Neural Information Processing Systems*.
- Cho, W. I., Kim, J. W., Kim, S. M., and Kim, N. S. (2019). On Measuring Gender Bias in Translation of Gender-neutral Pronouns.
- Devlin, J., Chang, M.-W., Lee, K., and Toutanova, K. (2019). BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding.
- Google (2018). Reducing gender bias in Google Translate. <https://blog.google/products/translate/reducing-gender-bias-google-translate/>.
- Kappl, M. (2025). Are All Spanish Doctors Male? Evaluating Gender Bias in German Machine Translation.
- Lardelli, M., Attanasio, G., and Lauscher, A. (2024). Building Bridges: A Dataset for Evaluating Gender-Fair Machine Translation into German. In *Findings of the Association for Computational Linguistics ACL 2024*, pages 7542–7550, Bangkok, Thailand and virtual meeting. Association for Computational Linguistics.
- Lin, G. H.-c. and Chien, P. S. C. (2009). Machine Translation for Academic Purposes. *Proceedings of the International Conference on TESOL and Translation 2009*, pages pp.133–148.

## Bibliography

- Prates, M. O. R., Avelar, P. H. C., and Lamb, L. (2019). Assessing Gender Bias in Machine Translation – A Case Study with Google Translate.
- Rescigno, A. A. and Monti, J. (2023). Gender Bias in Machine Translation: A statistical evaluation of Google Translate and DeepL for English, Italian and German. In *Proceedings of the International Conference on Human-informed Translation and Interpreting Technology 2023*, pages 1–11, UNIOR NLP Research Group, University of Naples "L'Orientale", Naples, Italy. INCOMA Ltd., Shoumen, Bulgaria.
- Savoldi, B., Bastings, J., Bentivogli, L., and Vanmassenhove, E. (2025). A decade of gender bias in machine translation. *Patterns*, page 101257.
- Savoldi, B., Papi, S., Negri, M., Guerbero-f-Arenas, A., and Bentivogli, L. (2024). What the Harm? Quantifying the Tangible Impact of Gender Bias in Machine Translation with a Human-centered Study. In *Proceedings of the 2024 Conference on Empirical Methods in Natural Language Processing*, pages 18048–18076, Miami, Florida, USA. Association for Computational Linguistics.
- Schiebinger, L. (2014). Scientific research must take gender into account. *Nature*, 507(7490):9–9.
- Schmitz, D. (2022). In German, all professors are male.
- Schryen, G. (2015). Writing Qualitative IS Literature Reviews—Guidelines for Synthesis, Interpretation, and Guidance of Research. *Communications of the Association for Information Systems*, 37.
- Schwemmer, C., Knight, C., Bello-Pardo, E. D., Oklobdzija, S., Schoonvelde, M., and Lockhart, J. W. (2020). Diagnosing Gender Bias in Image Recognition Systems. *Socius*, 6:2378023120967171.
- Sczesny, S., Formanowicz, M., and Moser, F. (2016). Can Gender-Fair Language Reduce Gender Stereotyping and Discrimination? *Frontiers in Psychology*, 7.
- Shrestha, S. and Das, S. (2022). Exploring gender biases in ML and AI academic research through systematic literature review. *Frontiers in Artificial Intelligence*, 5:976838.
- SkyQuest (2025). Machine Translation (MT) Market Size, Growth & Trends Report | 2032. <https://www.skyquestt.com/report/machine-translation-market>.

## Bibliography

- Smacchia, M., Za, S., and Arenas, A. (2024). Does AI Reflect Human Behaviour? Exploring the Presence of Gender Bias in AI Translation Tools. In Braccini, A. M., Ricciardi, F., and Virili, F., editors, *Digital (Eco) Systems and Societal Challenges*, volume 72, pages 355–373. Springer Nature Switzerland, Cham.
- Soundararajan, S. and Delany, S. J. (2024). Investigating Gender Bias in Large Language Models Through Text Generation. *Association for Computational Linguistics*, Proceedings of the 7th International Conference on Natural Language and Speech Processing (ICNLSP 2024):410–424.
- Stanczak, K. and Augenstein, I. (2021). A Survey on Gender Bias in Natural Language Processing.
- Stanovsky, G., Smith, N. A., and Zettlemoyer, L. (2019). Evaluating Gender Bias in Machine Translation.
- Thompson, B., Dhaliwal, M. P., Frisch, P., Domhan, T., and Federico, M. (2024). A Shocking Amount of the Web is Machine Translated: Insights from Multi-Way Parallelism.
- United Nations (2023). Achieve Gender Equality And Empower All Women and Girls. <https://sdgs.un.org/goals/goal5>.

## Appendix

## Bibliography

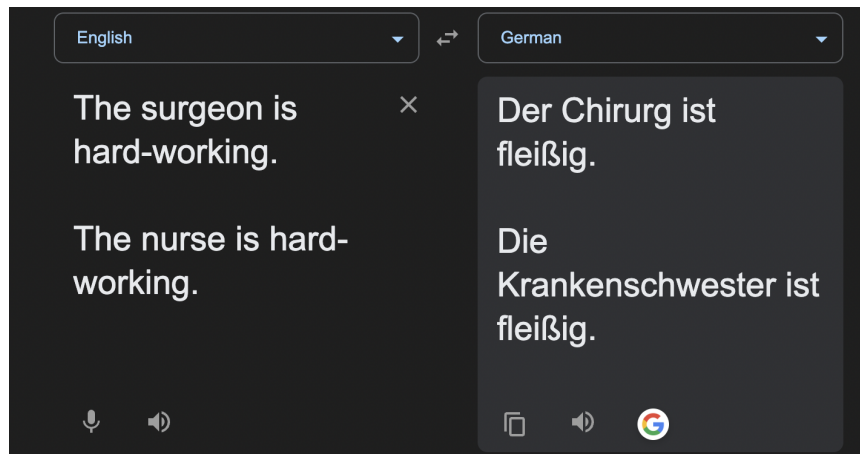


Figure 1: Google Translate assigns stereotypical genders to occupational roles.

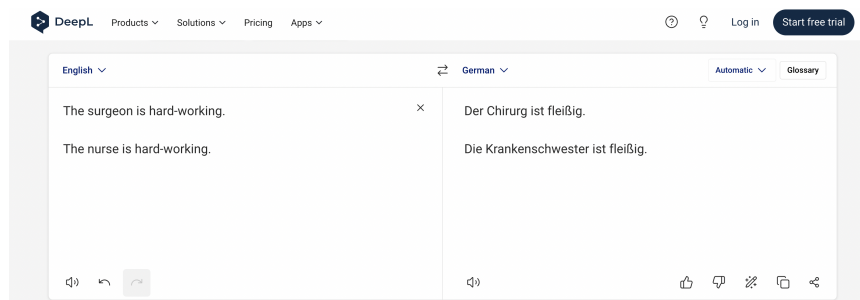


Figure 2: DeepL shows a similar bias in the same sentence, highlighting consistent patterns across MT tools.

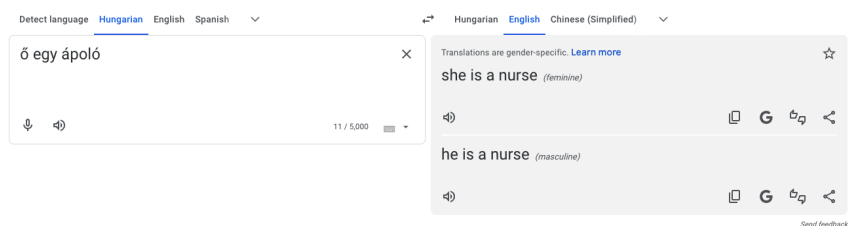


Figure 3: Gender-specific translation by Google Translate for ambiguous pronouns.

1. Hiermit versichere ich,

- dass ich die von mir vorgelegte Arbeit selbständig abgefasst habe,
- dass ich keine weiteren Hilfsmittel verwendet habe als diejenigen, die im Vorfeld explizit zugelassen und von mir angegeben wurden,
- dass ich die Stellen der Arbeit, die dem Wortlaut oder dem Sinn nach anderen Werken (dazu zählen auch Internetquellen und KI-basierte Tools) entnommen sind, unter Angabe der Quelle kenntlich gemacht habe und
- dass ich die vorliegende Arbeit noch nicht für andere Prüfungen eingereicht habe.

2. Mir ist bewusst,

- dass ich diese Prüfung nicht bestanden habe, wenn ich die mir bekannte Frist für die Einreichung meiner schriftlichen Arbeit versäume,
- dass ich im Falle eines Täuschungsversuchs diese Prüfung nicht bestanden habe,
- dass ich im Falle eines schwerwiegenden Täuschungsversuchs ggf. die Gesamtprüfung endgültig nicht bestanden habe und in diesem Studiengang nicht mehr weiter studieren darf und
- dass ich, sofern ich zur Erstellung dieser Arbeit KI-basierter Tools verwendet habe, die Verantwortung für eventuell durch die KI generierte fehlerhafte oder verzerrte (bias) Inhalte, fehlerhafte Referenzen, Verstöße gegen das Datenschutz- und Urheberrecht oder Plagiate trage.

Berlin, den June 6, 2025

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(Unterschrift des Verfassers)