B. Sc. Information Systems

Bachelor's Thesis

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

Khanh Linh Pham

Supervisors: Prof. Dr. Diana Hristova, Prof. Dr. Markus Schaal

Semester: Summer Semester 2025
Matrikel-Nr.:   77211916753
Email: klpham04@gmail.com

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Abstract

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1 Introduction

Machine Translation (MT) helps millions of people communicate across languages, in daily life and in areas like healthcare, law, and business (**?**). Services like Google Translate handle over 200 million users every day (**??**). It is a fast-growing market. A report by **?** valued it at 980 million USD in 2023, with projections reaching 2.78 billion USD. New and more advanced translation models keep appearing, and many of them are free to use. As a result, MT tools are now used to translate large volumes of content across domains.

With this widespread use, the output of MT systems increasingly shapes how people receive and interpret information. But automatic translations are not neutral. There is growing concern about the social effects of biased translations. One key issue is gender bias. MT systems are often trained on large datasets that reflect social norms and stereotypes. If the data contains gender bias, the system will likely reproduce it (**???**).

A common case is the use of gendered terms in translations of gender-neutral input. For example, the English sentence "The nurse is hard-working" does not say anything about gender. But a translation system may render it in German as "Die Krankenschwester ist fleißig," which uses the explicitly feminine term *Krankenschwester*. Similarly, "The surgeon is hard-working" may become "Der Chirurg ist fleißig," using the masculine form *Chirurg*. These choices add gendered assumptions that were not present in the original. Such patterns are not just technical side effects. They can reinforce stereotypes, especially when they appear in job ads, reports, or other public texts.

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, translations often reflect traditional roles, like associating "nurse" with women and "surgeon" with men. This can affect people's perceptions of jobs and reinforce gender roles.

When used in formal contexts like job descriptions or reference letters, biased translations can shape how a candidate is perceived. If a system always assigns male pronouns to

leadership roles and female terms to caregiving roles, it may disadvantage those who do not match those stereotypes (**?**). This is not just a personal issue. It can reduce diversity and go against 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 (**??**).

Language also shapes thought. Research shows that readers often interpret masculine forms as male-specific, even if they are supposed to be generic (**?**). Inclusive forms are more common in official documents, less so in everyday language. However, exposure matters. Frequent use of fair language makes it feel more normal. Detecting and addressing bias in MT can support this shift.

1.1.2 Why Detection Systems Are Needed

Current research on this topic tends to focus more on the quantitative measurement of gender bias (**???**). Common methods include counting gendered forms in outputs and comparing them to demographic baselines or human expectations (**???**). These are useful, but they do not help users identify specific biased translations in real-time. Evaluations are not enough for accountability.

Other domains, like facial recognition, have already seen progress in active bias detection. For example, **?** showed that systems tend to label women more accurately if they match stereotypical appearances (e.g., long hair). Some models even linked female images to words like "kitchen" or "cake" based on bias patterns in training data. For MT, a detection layer is still missing. Without such tools, biased translations are likely to spread unnoticed. A detection system could flag potential bias in real time, improving transparency and encouraging more careful use.

1.2 Problem Statement and Research Questions

DRAFT NEED TO REWRITE AFTER IMPLEMENTATION This thesis focuses on gender bias in English-to-German (EN-DE) MT. This language pair is widely used in research, with many open datasets and high-quality models available. It also involves a grammatical shift: English has limited gender marking, while German assigns gender to many nouns and pronouns. This structural difference makes gender bias more visible and easier to study in the translation outputs.

The core problem boils down to the significant bias towards the masculine form in EN-DE MTs, sometimes consituting 93-96% of translations for isolated words (**?**). These outputs

often reflect social stereotypes rather than objective translations, yet current systems offer no mechanism to detect or signal when such bias occurs (**?**). 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.

The translation system used is Opus-MT, an open-source neural MT model. It is widely used in research, supports EN-DE translation, and is trained on real-world corpora, making it suitable for studying translation bias (**?**). Translations are then 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 (**?**). The final tool highlights biased parts in a simple web demo. The goal is not a perfect classifier but a working prototype that shows how such detection could be integrated into translation workflows.

The main research question is therefore: **"How can a NLP-based binary classification model detect gender bias in English-German translations?"**.

1.3 Scope

WRITE AFTER IMPLEMENTATION PART This thesis focuses only on EN-DE MT. Other language pairs are out of scope.

1.4 Limitations

WRITE AFTER IMPLEMENTATION PART It becomes especially difficult to detect when sentences contain multiple subjects, indirect references, or ambiguous pronouns. For example, as **?** 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 (**?**). 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.

1.5 Overview of Chapters

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2 Theoretical Background and Related Work

This section outlines key findings of related work on gender bias in MT, with a focus on the English-German (EN-DE) 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.

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 **?** and was further informed by **?** and **?**, 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 **??**. Key search terms consisted of *gender bias*, *machine translation*, *AI*, *machine learning*, *German*, *stereotypes*, and *detection*, which were combined with *AND/OR*. 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
Foundations of Gender Bias in Natural Language Processing	Traces early research that identified gender bias in language. Focuses on foundational studies that showed why the issue matters and how later work builds on these findings.
Sources and Manifestations of Bias	Explains how stereotypes shape language and persist over time. Describes how societal bias enters training data, model design, and system feedback. Shows how bias appears in machine translation and everyday language.
Linguistic Challenges in English-German Translations	Explores key grammatical differences between English and German that affect translation. Focuses on how the lack of gender in English and its presence in German can lead to biased outputs.
Mitigation Strategies and Current Limitations	Reviews how current research tries to reduce gender bias in NLP. Highlights what these methods can and cannot do. Helps identify where a classification-based approach could fill gaps and improve bias detection 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. Beyond these systematic methods, I also included supplementary sources when needed while writing. These consist of contextual references, statistics, or secondary citations that support specific points but were not part of the core conceptual or methodological framework. Supplementary sources were defined as materials identified outside the systematic search, such as papers found through backward citations or targeted queries for statistics and news, which provided support for subordinate arguments without being central to the study's theoretical or analytical structure.

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. Sources also had to be available in full text without access restrictions. **Exclusion criteria** filtered out studies focusing on general NLP bias without a direct link to MT, non-gender biases, and highly technical papers lacking contribution to the general understanding of gender bias or that did not provide additional knowledge beyond what was already found in previously published papers. 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 Understanding Gender Bias in English-to-German Machine Translation

2.2.1 Defining Natural Language Processing and Machine Translation

Natural Language Processing (NLP) refers to the development of machine systems that can understand and generate human language. The goal is to mimic and understand it as fluently as possible (**??**). Common applications include chatbots, translation tools, speech recognition, and image captioning.

MT is a direct application of NLP. It refers to the automated translation of text from one language to another (**?**). MT systems have gone through several stages of development, each with its own limitations. Earlier approaches like rule-based and statistical MT used manually defined grammar rules or pattern matching from large translation corpora (**?**). These systems often struggled with full sentences and complex expressions. For example, "She gave him a hand" might be translated literally, missing its idiomatic meaning. This happens because the system fails to capture context and phrase-level meaning.

Most modern systems, including Google Translate and DeepL, use neural machine translation (). These systems are trained on large sets of translated texts. They learn to represent the meaning of whole sentences as mathematical structures and generate more fluent and accurate translations. Unlike earlier systems, they consider the full context of a sentence, which helps reduce errors and improves the handling of ambiguous or idiomatic language.

Neural networks have made machine translation more flexible, context-aware, and closer

to how humans understand language.

2.2.2 What is Gender Bias in Machine Translation?

2.3 Societal Relevance and Impact of Gender Bias in Machine Translation

2.4 Research Gaps in Gender Bias Detection for English-to-German Machine Translation

2.5 Approach and Justification of the Technical Setup

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

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<div style="text-align: center">*Bibliography*</div>

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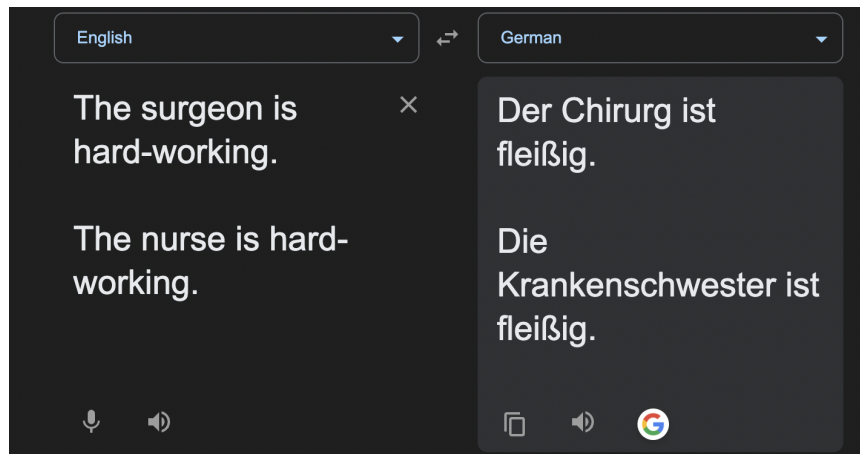
Appendix

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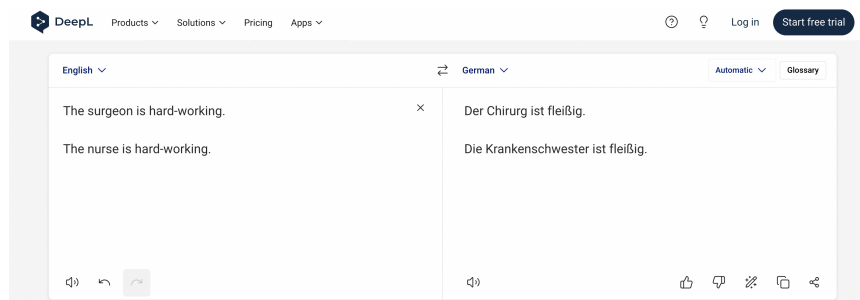

Figure 2: DeepL shows a similar bias in the same sentence, highlighting consistent patterns across MT tools.
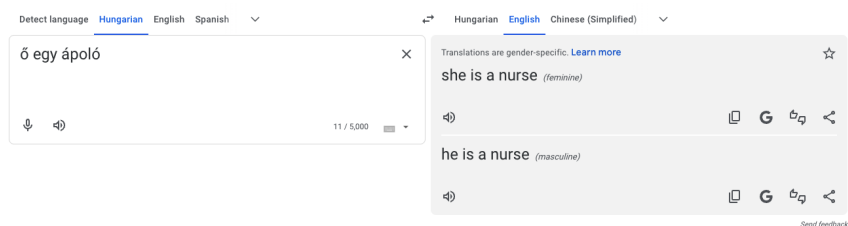

Figure 3: Gender-specific translation by Google Translate for ambiguous pronouns.

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 29, 2025

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