

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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Semester: Summer Semester 2025

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Date: xx.xx.2025

Abstract

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Sperrvermerk

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Berlin, den 01. Januar 2099

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(Unterschrift des Verfassers)

Contents

List of Figures	vi
List of Tables	vii
1 Introduction	1
1.1 Motivation	1
1.1.1 Social and Ethical Importance of Addressing Gender Bias	1
1.1.2 Why Detection Systems Are Needed	2
1.2 Problem Statement and Research Questions	2
1.3 Scope	3
1.4 Limitations	3
1.5 Overview of Chapters	4
2 Theoretical Background and Related Work	5
2.1 Literature Search Process	5
2.1.1 Search Sources and Tools	5
2.1.2 Literature Review Framing	5
2.1.3 Citation Tracking	6
2.1.4 Selection Criteria and Screening Process	7
2.2 Understanding Gender Bias in English-to-German Machine Translation . .	7
2.2.1 Natural Language Processing and Machine Translation	7
2.2.2 Bias in Machine Translation Systems	8
2.2.3 What Gender Bias Means in Machine Translation	9
2.2.4 Manifestations of Gender Bias	9
2.2.5 Linguistic Challenges in English-German Translation	11
2.2.6 German Gender-Fair Language	11
2.3 Societal Relevance and Impact of Gender Bias in Machine Translation . .	12
2.3.1 Foundational studies	12
2.3.2 Why it matters	13
2.4 Research Gaps	14

Contents

2.5	Approach and Justification of the Technical Setup	14
2.5.1	Binary Classification in NLP	14
2.5.2	Transformer Architecture	15
2.5.3	Pre-trained Language Model: BERT	15
3	Conceptual Framework	17
	Bibliography	18

List of Figures

2.1	Frequency of different types of gender-inclusive language. Source: Waldendorf (2024) p. 367.	12
2.2	Study design. Post-editing of an MT output into both feminine and masculine gender. Source: Savoldi et al. (2024) p. 18048	14
2.3	Architecture of the Transformer model, composed of an encoder and a decoder. Source: Xiao and Zhu (2023) p. 6.	16
1	Google Translate assigns stereotypical genders to occupational roles.	23
2	DeepL shows a similar bias in the same sentence, highlighting consistent patterns across MT tools.	23
3	Gender-specific translation by Google Translate for ambiguous pronouns.	23

List of Tables

2.1	Key concepts relevant to this thesis	6
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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 (Kappl 2025). Services like Google Translate handle over 200 million users every day (Prates et al. 2019; Shrestha and Das 2022). It is a fast-growing market. A report by SkyQuest (2025) 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 (Cho et al. 2019; Soundararajan and Delany 2024; Smacchia et al. 2024).

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 (Prates et al. 2019; Cho et al. 2019; Rescigno and Monti 2023). 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 (Bolukbasi et al. 2016). 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 (Sczesny et al. 2016; United Nations 2023).

Language also shapes thought. Research shows that readers often interpret masculine forms as male-specific, even if they are supposed to be generic (Sczesny et al. 2016). 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 (Rescigno and Monti 2023; Barclay and Sami 2024; Smacchia et al. 2024). Common methods include counting gendered forms in outputs and comparing them to demographic baselines or human expectations (Rescigno and Monti 2023; Prates et al. 2019; Savoldi et al. 2024). 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, Schwemmer et al. (2020) 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 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.

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 (Tiedemann and Thottingal 2020). 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 (Devlin et al. 2019). 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 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.

1.5 Overview of Chapters

WRITE AFTER IMPLEMENTATION PART

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 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*, 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

This section explains the key terms and concepts needed to understand gender bias in English-to-German MT. It defines important ideas like natural language processing (NLP), MT, and gender bias. These concepts provide the background necessary to follow the thesis.

2.2.1 Natural Language Processing and Machine Translation

NLP refers to the development of machine systems that can process and generate human language. The goal is to mimic and understand it as fluently as possible (Smacchia et al. 2024; Ullmann 2022). Common applications are chatbots, translation tools, speech recognition, and image captioning.

MT is a direct application of NLP. It is used to automatically translate text from one language to another (Lin and Chien 2009). MT systems have gone through several stages of development; earlier approaches like rule-based and statistical MT used manually defined grammar rules or pattern matching from large translation corpora (Chakravarthi et al. 2021). For example:

"The girl reads a book" → "Das Mädchen liest ein Buch"

Rules: "girl" → "Mädchen", "reads" → "lesen", "book" → "Buch"

These systems often struggled with full sentences and complex expressions because they fail to capture context and phrase-level meaning. "She gave him a hand" might be translated

literally, missing its idiomatic meaning.

Most modern systems, including Google Translate and DeepL, use **neural machine translation (NMT)** (Wu et al. 2016; DeepL 2021). 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 aim to consider the full context of a sentence, which helps reduce errors and improves the handling of ambiguous or idiomatic language.

2.2.2 Bias in Machine Translation Systems

Similarly to how humans are shaped by their environment, MT models learn from data they are trained on. Existing biases are thus reflected and reinforced in the final models, creating "machine bias" (Stanczak and Augenstein 2021; Smacchia et al. 2024). Shah et al. (2020), as described by Ullmann (2022), differentiates between four origins of biases affecting NLP systems:

- **Selection Bias:** Happens when the training data does not reflect the context in which the model is used (e.g., using Wikipedia data for detecting harmful language on Twitter).
- **Label Bias:** Occurs when annotations in the dataset are incorrect or skewed. This can be influenced by the annotators' own biases or lack of awareness of diverse linguistic expressions.
- **Model Overamplification:** During training, models can exaggerate patterns found in the data. If a dataset predominantly associates cooking with women, the assumption can be reinforced that cooking is an activity exclusive to women.
- **Semantic Bias:** Stems from associative relationships within the data, where certain words or phrases are frequently co-occurring with specific genders (e.g., "he" with "doctor").

Ullmann (2022) notes that the scale of training data (e.g., 175 billion parameters for GPT-3) makes it practically impossible to review all of it, allowing misinformation or offensive content to be reproduced by the system. The author also points out that platforms like Wikipedia and Reddit are male-dominated and often contain harmful or false content.

2.2.3 What Gender Bias Means in Machine Translation

A clear definition of gender bias has not yet been established (Stanczak and Augenstein 2021). Determining which features in text indicate bias is difficult, and the characteristics of non-biased text are often unclear. This makes it challenging to hold users accountable for gender bias, detect all harmful signals, and develop standard evaluation benchmarks (Barclay and Sami 2024; Shrestha and Das 2022; Stanczak and Augenstein 2021).

Since there is no clear definition, this work defines gender bias based on specific manifestations described in the following subsection. Any text that exhibits one or more of these forms will be considered gender biased.

2.2.4 Manifestations of Gender Bias

This section draws from the main studies analyzing gender bias in EN-DE MT (Ullmann 2022; Rescigno and Monti 2023; Lardelli et al. 2024; Kappl 2025). Since existing research does not clearly define the different manifestations, the findings are grouped here into three main categories.

Defaulting to Masculine Forms

In both singular and plural contexts, the *generic masculine* refers to the default use of the masculine grammatical gender. For example, the sentence "Die Studenten sind im Hörsaal" (translation: "The students are in the lecture hall") uses the masculine plural form to refer to a group of students regardless of their gender.

It is commonly used in spoken German (Lardelli et al. 2024; Schmitz 2022), although research has consistently shown that the generic masculine creates a male bias in mental representations, leading readers or listeners to think more of male than female examples (Sczesny et al. 2016). In MT, the generic masculine can lead to inaccurate or unfair representations of gender in translated text. Rescigno and Monti (2023) observed a predominance of masculine forms in translation outputs (approximately 90% in Google Translate and 85–88% in DeepL for EN-IT and EN-DE), even when the original sentences contained relatively few masculine references. This shows that the bias is not minor but occurs quite heavily in those systems.

Reinforcement of Stereotypes

Stereotypes and gender roles stem from historical and cultural perceptions of men’s and women’s societal roles, many of which are obsolete but still influential. For example, when

men and women often take on different roles at work and at home, it shapes how people think about their personalities and qualities. Correspondence bias can emerge, where people infer attributes from observable behaviours (Godsil et al. 2016). These associations can then be reinforced by popular media, such as TV and advertisements (Godsil et al. 2016), just as much as it can be influenced by MT tools.

A common manifestation of this are **stereotypical job associations**. This can be seen in cases where models assign he/him pronouns to roles like doctors and pilots, and she/her pronouns to roles like nurses and flight attendants (Shrestha and Das 2022), with an even stronger tendency in male-dominated fields such as STEM (Prates et al. 2019). In addition, NLP models have also been shown to **link certain adjectives and traits to genders**. Traits like "masterful," "assertive," and "competitive" are often associated with men, while "friendly," "unselfish," and "emotionally expressive" are more commonly linked to women (Godsil et al. 2016).

Neglecting Contextual Information

Coreference resolution refers to the process of using contextual information to determine the correct gender in translation (Stanczak and Augenstein 2021). In MT, this means identifying links between words like pronouns and the nouns they refer to. While human translators use both linguistic cues (such as pronouns and grammar) and real-world knowledge to correctly assign gender (Rescigno and Monti 2023), MT systems often fail to do so reliably, especially when gender information appears earlier in the text or across sentence boundaries (Cho et al. 2019; Stanovsky et al. 2019). For example, if a biography introduces a person with a female name at the beginning, but later refers to that person only by name, translation systems may lose the link and default to masculine forms for the remaining text.

Rescigno and Monti (2023) found that including previous sentences improved coreference resolution and reduced masculine defaults, though some systems benefited more than others. However, the use of context also introduced occasional new errors. Additionally, Savoldi et al. (2024) highlighted that correcting biased translations toward feminine forms required significantly more time and edits than masculine ones, revealing a notable cost disparity.

Similarly, Lardelli et al. (2024) showed that even with natural passages from Wikipedia and Europarl, systems still largely defaulted to masculine forms. Feminine and inclusive translations remained rare, while gender-neutral alternatives appeared mainly when the noun itself suggested them.

2.2.5 Linguistic Challenges in English-German Translation

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 nouns: "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" (m) and "actress" (f), 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. Note that grammatical gender has no connection to societal or biological gender. It is a rule of the language rather than a reflection of identity. For example, the German word Mädchen (girl) is grammatically neuter and takes the article "das". This is not because the referent lacks gender, but because the suffix "-chen" automatically assigns neuter gender. Grammatical gender in German follows structural rules, even when they contradict real-world gender associations.

2.2.6 German Gender-Fair Language

Gender-fair language (GFL) refers to the use of language that treats all genders equally and aims to reduce stereotyping and discrimination (Sczesny et al. 2016). Three common approaches to plural mentionings in German are:

- **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 cannot be consistently applied (Lardelli et al. 2024).
- **Gender-inclusive characters:** This combines masculine, feminine and non-binary forms by using a character like *, :, or __, e.g., *die Student*innen lernen*. This method is consistent but may interrupt reading flow and lacks standardization (Lardelli et al. 2024).
- **Pair form:** This names both gender forms, e.g., *die Studentinnen und Studenten lernen*. It is currently the most used GFL form in German (Waldendorf 2024), briefly surpassing the star and colon characters as seen in Figure 2.1.

These examples apply when the gender of the subjects is ambiguous. But when gender is known, especially in singular mentions, the generic masculine should be avoided. However,

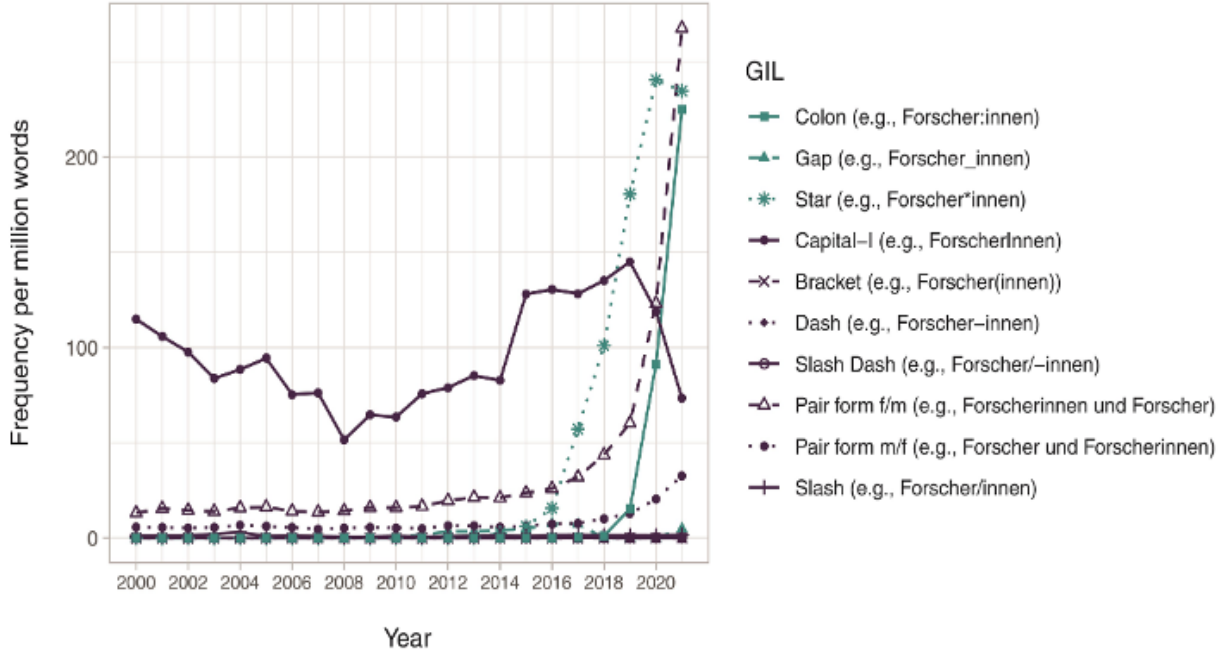


Figure 2.1: Frequency of different types of gender-inclusive language. Source: Waldendorf (2024) p. 367.

in the same way as gender bias has no clear definition, there is **no agreed standard for GFL** (Lardelli et al. 2024; Savoldi et al. 2025). "Fairness" therefore heavily depends on personal views, culture, and context, which raises ethical questions about debiasing systems.

2.3 Societal Relevance and Impact of Gender Bias in Machine Translation

This section outlines why gender bias is a subject of research in the first place and where it connects to broader social and ethical questions. It first looks at early studies that brought attention to gender patterns in language technologies and raised awareness of their social impact. Understanding these origins helps explain why it continues to be relevant today.

2.3.1 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 study using Google Translate to translate sentences like "[Gender-neutral pronoun] is an engineer" from twelve gender-neutral languages into English. The results showed a strong bias toward male pronouns, especially in STEM occupations. This could not be explained by real-world labor statistics, pointing instead to imbalances in the system's training data. The study received wide media attention, leading Google to change their translation policy: Google Translate began showing both feminine and masculine forms for ambiguous inputs (Google 2018) (see Figure 3).

Building on this, **Stanovsky et al. (2019)** created WinoMT, a benchmark for evaluating gender bias in English-to-multilingual translations. It focused on occupations in contexts designed to challenge stereotypes. The study found that systems were more accurate for stereotypical gender roles but struggled in non-stereotypical cases, confirming the trends observed by Prates et al.. Together, these studies helped spark the ongoing research interest in gender bias in MT.

2.3.2 Why it matters

Gender bias in MT can lead to **representational harm**, meaning biased or reductive portrayals of a particular gender continue to spread (Stanczak and Augenstein 2021).

It also contributes to the invisibility of women in male-dominated professions (Kappl 2025). Studies show that biased language in machine-generated text, such as children's stories or job ads, can **influence how young people view themselves** (Soundararajan and Delany 2024; Kappl 2025). It may shape their interests, hobbies, and career choices. This is especially visible in STEM fields (Prates et al. 2019), where stereotypes are more persistent. When job descriptions or mock interviews use gender-exclusive pronouns, women report feeling less belonging, lower motivation, and weaker identification with the role (Godsil et al. 2016). Many self-select out of applying, shrinking the female talent pool and **reinforcing gender gaps in the workforce**.

Research also shows that using GFL like "she and he" or "one" can improve how women respond to job ads. It reduces stereotype threat and helps them engage more positively with opportunities (Godsil et al. 2016). Using inclusive language can therefore offer both social and competitive benefits for companies.

Furthermore, a study by Savoldi et al. (2024) 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

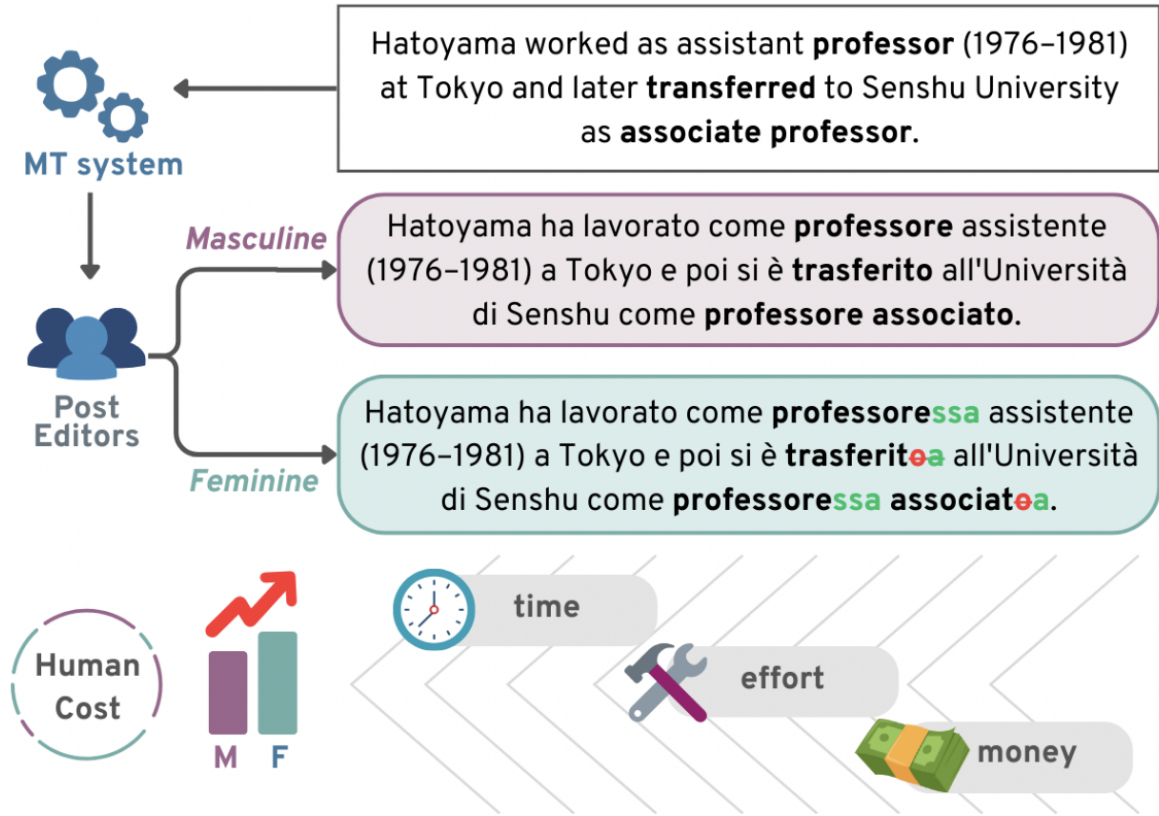


Figure 2.2: Study design. Post-editing of an MT output into both feminine and masculine gender. Source: Savoldi et al. (2024) p. 18048

to masculine counterparts (Figure 2.2). 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.

2.4 Research Gaps

2.5 Approach and Justification of the Technical Setup

2.5.1 Binary Classification in NLP

Binary Classification means categorizing whether an element belongs into a distinct class. It is the most common task in ML and is frequently found in every day life, such as automatically filtering e-mails as "spam" or "not spam" (Quemy 2019). The ML algorithms

use information from past examples to create a model or find key rules for making correct decisions. **This thesis attempts to label a translation as "potentially gender biased" or "neutral".**

As explained in subsection 2.2.3, since there is no clear definition of what counts as gender biased, there is also no clear definition of what is unbiased. I have set rules for what I consider biased, but that does not mean everything else is automatically unbiased. For this reason, I use the term "neutral" instead.

2.5.2 Transformer Architecture

Transformer models are a type of neural network architecture commonly used for NLP tasks. They *transform* an input sequence into an output sequence, such as in translation. To effectively achieve that, they deploy a **self-attention mechanism** (Phuong and Hutter 2022). It allows the model to consider all elements of the input at once (e.g., words of a sentence), rather than processing them separately. As a result, the model can capture global dependencies and contextual relationships more accurately. For example, in the sentence “The dog chased the ball because it was fast,” the model can learn that “it” refers to “the dog” by attending to the relevant parts of the sentence simultaneously.

The transformer architecture follows the general **encoder-decoder** framework. Figure 2.3 Xiao and Zhu (2023) gives an overview of its components.

The **encoder**’s job is to read the input sentence and turn it into a series of vectors the model can understand. Each vector is a list of numbers representing the meaning and structure of each word. It starts with input embeddings and positional encodings to handle word meaning and order (bottom left hand side of the Figure 2.3). Then it passes the data through multiple identical layers; each including *multi-head self-attention*. This mechanism runs several self-attention processes in parallel, with each *head* learning to capture different aspects to give the model a more complete understanding of the sentence. The layer also includes a *feed-forward network*, which processes each word vector individually. It acts like a small filter that sharpens the information for each word. Each layer refines the output of the previous one to help the model gradually build up more complex and abstract representations of the input.

The **decoder** then generates the output sentence using the encoder’s output. Since BERT only uses the encoder part of the Transformer though, the decoder is not relevant here.

2.5.3 Pre-trained Language Model: BERT

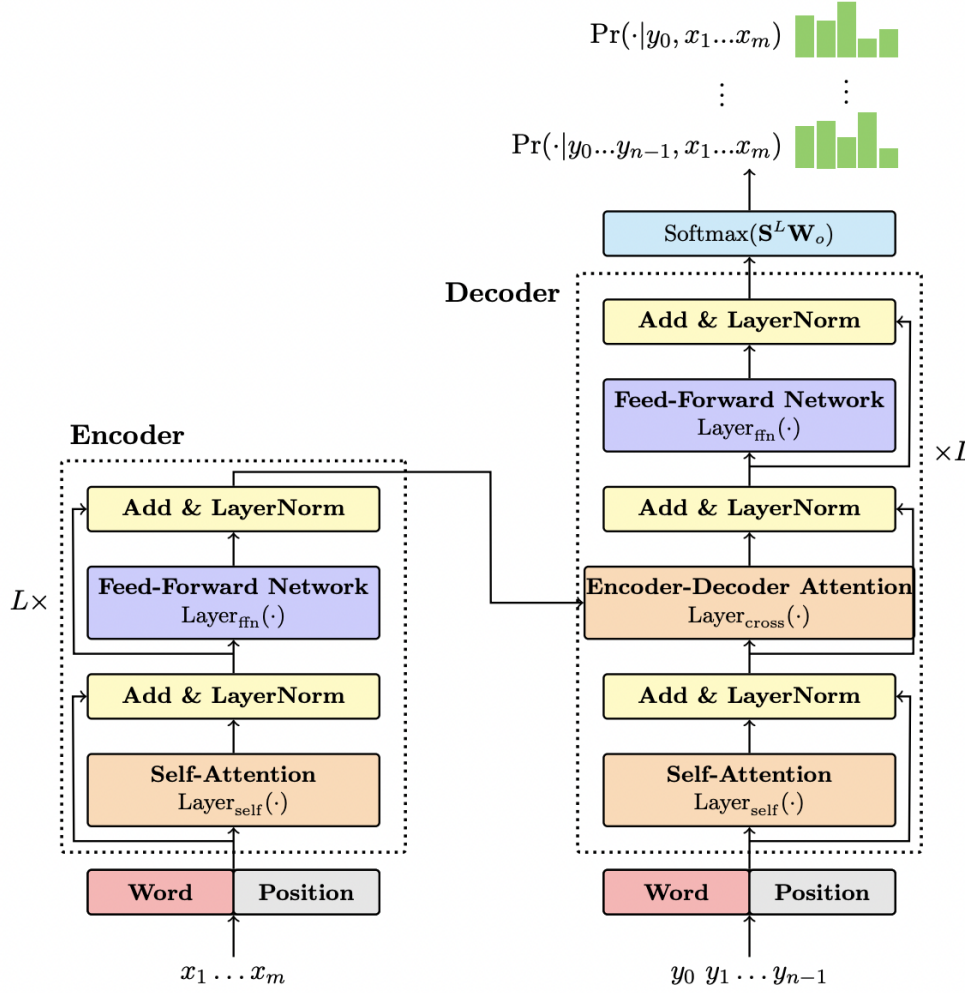


Figure 2.3: Architecture of the Transformer model, composed of an encoder and a decoder.
Source: Xiao and Zhu (2023) p. 6.

3 Conceptual Framework

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Appendix

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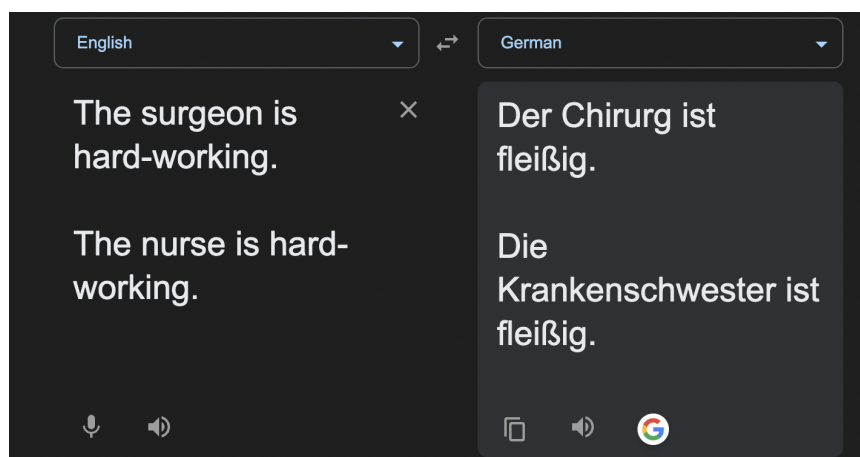


Figure 1: Google Translate assigns stereotypical genders to occupational roles.

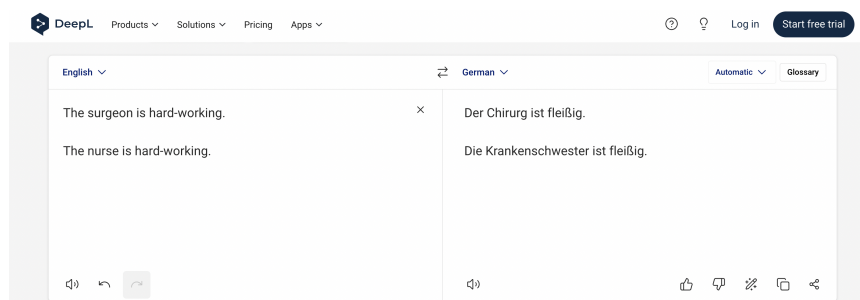


Figure 2: DeepL shows a similar bias in the same sentence, highlighting consistent patterns across MT tools.

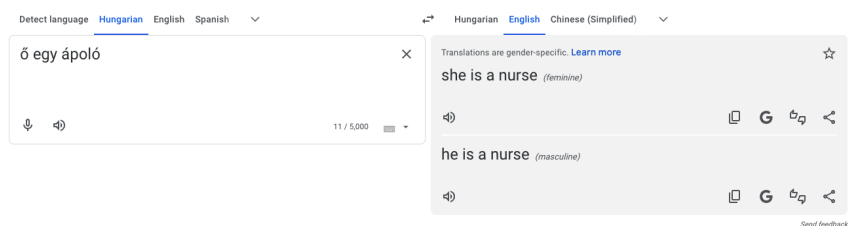


Figure 3: Gender-specific translation by Google Translate for ambiguous pronouns.

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 July 10, 2025

.....
(Unterschrift des Verfassers)