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

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Abstract

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List of Abbreviations

EN-DE   English-to-German

GFL   Gender-Fair Language

mBERT   Multilingual BERT

MT   Machine Translation

NLP   Natural Language Processing

NMT   Neural Machine Translation

1 Introduction

Modern Machine Translation (MT) tools have made cross-lingual communication more accessible than ever. Services like Google Translate, used by over 200 million people daily (Prates et al., 2019; Shrestha and Das, 2022), offer fast and often accurate translations of full sentences and even longer texts. They are widely used in daily life as well as in fields such as healthcare, law, and business (Kappl, 2025).

The MT market continues to grow rapidly. A recent report by SkyQuest (2025) valued it at 980 million USD in 2023, with projections reaching 2.78 billion USD in the coming years. As the use of MT systems expands, their output has a growing impact on how users access and understand information, raising concerns about the quality and broader implications of these translations.

MT systems are trained on large-scale text corpora that often contain implicit social biases. Translation models tend to reproduce such patterns rather than correct them. One widely studied phenomenon is gender bias, which has been observed across different systems and language pairs (Cho et al., 2019; Soundararajan and Delany, 2024; Smacchia et al., 2024).

A common example is the use of gendered terms in the translation of gender-neutral sentences. The English input "The nurse is hard-working" does not specify gender, yet the German output may be "Die Krankenschwester ist fleißig," which assumes a female identity. In contrast, "The surgeon is hard-working" may be translated as "Der Chirurg ist fleißig," implying a male identity.

These translations introduce gendered information that was absent from the source text. When repeated across domains like job descriptions or media reporting, such patterns can reinforce societal stereotypes. This contradicts international standards set by organizations like the United Nations, UNESCO, and the European Union, which highlight inclusive language as essential for achieving the Sustainable Development Goals by 2030 (Sczesny et al., 2016; United Nations, 2023).

1.1 Motivation

The practical handling of such bias remains limited. Existing research has largely focused on measuring overall bias by counting gendered outputs, comparing them to expected patterns, or testing models on standard benchmarks (Rescigno and Monti, 2023; Barclay and Sami, 2024; Prates et al., 2019; Savoldi, Papi, et al., 2024). These studies provide insights into how often and in what forms bias appears, but they do not offer solutions for detecting biased translations as they occur.

The lack of established tools for real-time detection of gender bias is not a challenge unique to MT. In other domains, such as computer vision or automated hiring, studies have exposed similar

patterns. Image recognition systems, for example, have labeled portraits of women with terms like "girl," "cake," or "kitchen," while men received occupational labels like "attorney" or "executive" (Schwemmer et al., 2020). As long as biased translations remain hidden in individual outputs, they are likely to go unnoticed and unchallenged, underlining the need for methods making them visible to users.

1.2 Research Questions

Building on these challenges, this thesis aims to develop a system for detecting gender bias in English-to-German (EN-DE) translations using Natural Language Processing (NLP). The main goal is to create a transparent and efficient classifier that flags potentially biased outputs from MT. For this, a multilingual BERT model (mBERT), which processes text in multiple languages, will be manually fine-tuned for the task. The classifier will be integrated into a demo application that allows users to test bias detection in real time.

The focus on EN-DE was chosen because it is widely used in research, supported by numerous open datasets and high-quality models. Moreover, the linguistic differences between English and German highlight gender bias more clearly: English uses limited gender marking, while German requires gender assignment.

The following research questions structure the evaluation:

RQ1: How accurately does fine-tuning mBERT detect gender bias in EN-DE translations?

RQ2: What limitations arise in this detection system?

In line with similar studies in MT bias (e.g. Smacchia et al. (2024), Rescigno and Monti (2023)), RQ1 examines classifier performance using standard evaluation metrics. Overall accuracy on a held-out test set will be reported, along with precision and recall for the biased class and the F1-score to balance these measures.

RQ2 examines the main limitations of the detection system in realistic settings. First, ambiguous contexts such as unclear pronoun references and subtle gender cues will be tested to assess how they affect model decisions. Second, errors arising from grammatical gender in German, including incorrect noun-adjective agreement, will be analyzed. Third, the system's ability to generalize will be evaluated on out-of-domain texts. Finally, an error analysis will identify the most common failure modes and quantify their frequency in terms of false positives and false negatives.

1.3 Overview of Chapters

WRITE AFTER IMPLEMENTATION PART

2 Theoretical Background and Related Work

Detecting gender bias in EN-DE translations using NLP requires an understanding of what gender bias means in this context, how it appears in MT, and how it has been studied so far. To build this foundation, this chapter (1) defines the concept of gender bias in machine translation, (2) outlines its relevance, (3) identifies gaps in current research, and (4) justifies the technical design decisions made in this project.

Define Key Concepts

Review Related Work

Identify Research Gaps

Position Thesis Contribution

Explain Technical Approach
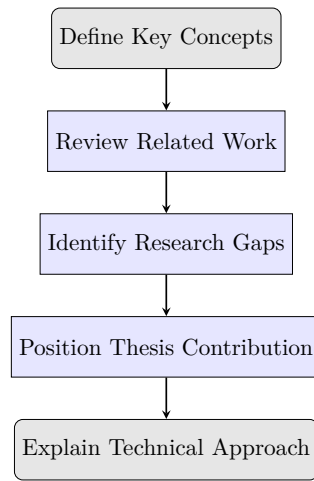
Figure 1: Overview of Chapter 2 Structure

2.1 Definitions

2.1.1 Natural Language Processing vs. Machine Translation

NLP enables machine systems to 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 performs automatic translation of text from one language to another (Lin and Chien, 2009). Over time, MT systems have developed from rule-based and statistical approaches, which depend on hand-crafted grammar rules or aligned sentence data, into more adaptable neural models (Chakravarthi et al., 2021).

Most modern systems, such as Google Translate and DeepL, rely on neural machine translation (NMT) (Y. Wu et al., 2016; DeepL, 2021). These models are trained on large collections of translated texts. They learn to represent the meaning of entire sentences as mathematical structures, enabling more fluent and accurate translations. Unlike earlier approaches, NMT systems take the full sentence context into account, which helps reduce errors and improves the handling of ambiguous or idiomatic language (Y. Wu et al., 2016). Throughout this work, all MT systems referenced or applied are neural models.

2.1.2 Bias in Society and its Manifestations

Bias refers to a tendency to favour or disadvantage certain individuals or groups based on preconceived ideas. It often comes from stereotypes, which are fixed and oversimplified ideas about a group. While stereotypes describe assumptions about people, bias influences actual behavior and treatment.

Bias takes many forms and can be based on characteristics such as age, disability, gender, ethnicity, religion, or sexual orientation (Ullmann, 2022). These biases often originate from longstanding cultural and historical beliefs about the expected behavior of different groups.

This study focuses specifically on gender bias. It is particularly prominent in machine translation due to the influence of gendered language. Elements such as gendered terms, occupational roles, and grammatical patterns can affect translations and often perpetuate stereotypes.

Drawing on key studies that examine gender bias in EN-DE MT (Ullmann, 2022; Rescigno and Monti, 2023; Lardelli et al., 2024; Kappl, 2025), such bias typically manifests in the following forms:

Defaulting to Masculine Forms

In both singular and plural contexts, the *generic masculine* uses the masculine grammatical gender as the default. 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 and other gendered languages (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).

Reinforcement of Stereotypes

The gendered language patterns discussed earlier reflect broader social beliefs about men's and women's roles in work and family life. Although many of these roles no longer reflect reality, they continue to shape judgments about people's abilities and personalities. This often leads to

correspondence bias, where traits are inferred based on behavior or circumstances (Godsil et al., 2016). Such stereotypes are reinforced by media, including television and advertising, and influence how language is used and understood.

One common result of this is stereotypical job associations. People often link roles like doctors or pilots with he/him pronouns, and roles like nurses or flight attendants with she/her pronouns (Shrestha and Das, 2022). Prates et al. (2019) also found clear patterns in how gender is associated with certain traits. Adjectives like "shy," "happy," "kind," and "ashamed" are often linked to women, while words like "arrogant," "cruel," and "guilty" are more often linked to men.

2.1.3 Gender Bias in Machine Translation

A clear definition of gender bias in MT does not exist, nor is there a standard method to identify indicative features in text (Barclay and Sami, 2024), which leads this study to use a simple rule-based definition to determine when a translation is gender biased.

- A gender-ambiguous subject in the source text is translated with a gendered term, often defaulting to the generic masculine (e.g., doctor → Arzt) or reflecting stereotypical gender roles (e.g., nurse → Krankenschwester).

- A gendered subject in the source text is assigned an incorrect gender in the translation, leading to semantic inconsistency (e.g., my mother is an engineer → meine Mutter ist ein Ingenieur).

This does not mean that all other cases are truly "unbiased". I will refer to anything that does not fall under these two cases as "neutral". This includes, but is not limited to:

- Sentences with no gendered terms, like "The weather is nice".

- Accurate translations of gendered input, like "The woman is a coder" → "Die Frau ist eine Programmiererin".

- The use of gender-fair alternatives (see subsection 2.2.6).

2.2 Related Works

While gender bias in MT has received increasing attention, research on the EN-DE language pair remains limited. Building on the earlier definitions, this part reviews relevant research to show how the field has approached the problem and where important gaps remain.

Biased Translation	Neutral/Fair Translation
Gender-ambiguous source is translated with a gendered term.	Gender ambiguity is preserved in the translation.
Gendered subject is assigned an incorrect gender.	Gender in the translation matches the gendered subject.
—	Use of gender-fair language alternatives (see subsection 2.2.6).

Table 1: Summary of gender bias scenarios in translation (original compilation)

2.2.1 Literature Search Process

For the literature review I combined incremental and conceptual literature review methods, where each source led to the identification of 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, Bastings, et al. (2025), who both conducted systematic reviews on gender bias in ML and MT respectively.

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.

Literature Review Framing

The four research aims were turned into key concepts, which are defined in Table 2. 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.

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.

Key Concept	Description
Defining Gender Bias in MT	Defines the core concept of gender bias in MT, including common bias patterns like gendered term insertion and incorrect gender assignments. Sets the conceptual foundation for the thesis.
Relevance and Existing Research	Establishes the importance of studying gender bias by reviewing related work. Highlights key findings and their implications for fairness.
Research Gaps and Open Challenges	Identifies the main gap: the absence of reliable detection systems for gender bias in EN-DE MT. Discusses the lack of a shared fairness definition and limitations in existing datasets.
Technical Design and Implementation	Explains the theoretical background and fundamental principles necessary to understand the implementation. Covers the underlying concepts that guide design choices and system functionality.

Table 2: Key concepts relevant to this thesis

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.

Selection Criteria and Screening Process

Titles and abstracts were manually screened to select relevant studies. Inclusion 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.

Inclusion Criteria	Exclusion Criteria
Addresses gender bias in MT	Focuses on general NLP bias without link to MT
Provides examples or discussion of gender-related errors	Covers non-gender-related biases
Explains the significance of gender bias in MT	Highly technical with no added general insight
Available in full text without access restrictions	Redundant or not contributing new perspectives

Table 3: Selection criteria for literature review

2.2.2 Foundational studies

First mentions of this issue date back to over a decade ago, having been recognized by a paper by Schiebinger (2014). Since then, there has been a general increase in research papers focusing on this topic, especially between 2019 and 2023 (Savoldi, Bastings, 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 labour 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 **??**).

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.

2.2.3 Biased Data Leading to Gender Errors

According to Ullmann (2022), translation errors often stem from biases present in the training data. The MT systems learns gender associations from word co-occurrences, such as "doctor" with masculine pronouns, causing incorrect or inserted gender in translations. It also amplifies existing biases during training like linking cooking predominantly with women, which leads to gendered outputs not supported by the input. The large size of training corpora increases the challenge of controlling data quality. Manual inspection becomes impractical when models are trained on hundreds of billions of tokens. Consequently, the model can unintentionally absorb and reproduce harmful or biased content, reinforcing patterns that lead to biased translations (Ullmann, 2022).

2.2.4 Ongoing Impact of Gender Bias in Machine Translation

These biases do not only cause translation errors but also have wider social consequences. They can lead to representational harm by repeatedly portraying certain genders in limiting or stereotypical ways (Stanczak and Augenstein, 2021). Since these biased outputs can re-enter the training data and influence future MT models, the cycle of biased representation continues and reinforces itself in society, creating a regressive feedback loop.
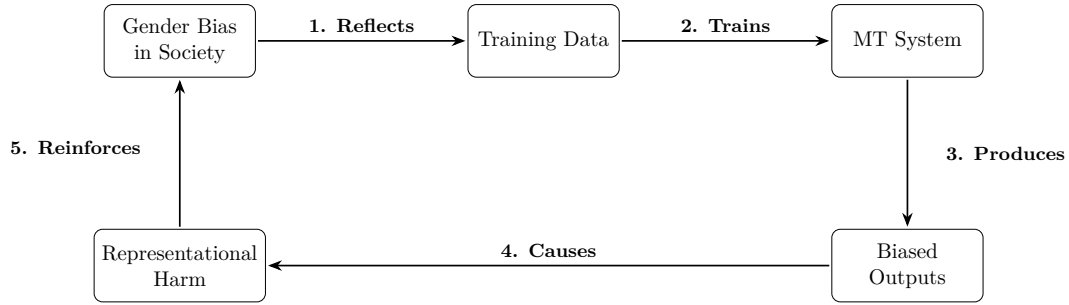

Figure 2: Regressive feedback loop of gender bias in MT

The generic masculine in particular leads to inaccurate and 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.

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 Gender-Fair Language (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).

Furthermore, a study by Savoldi, Papi, et al. (2024) measured how much effort people need to fix biased translations. They used metrics like the time it took to edit and how many edits were needed, based on human-targeted error rate. The results showed that fixing translations with feminine forms took almost twice as long and required four times more edits than those with masculine forms.

As a result, biased translations lead to higher economic costs and a quality gap that disproportionately affects women. Savoldi, Papi, et al. (2024) argued that current automatic bias metrics miss these human impacts. They called for better evaluation methods that reflect what users actually experience.

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 liguistic characteristcs. 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

GFL is 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 3.

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, in the same
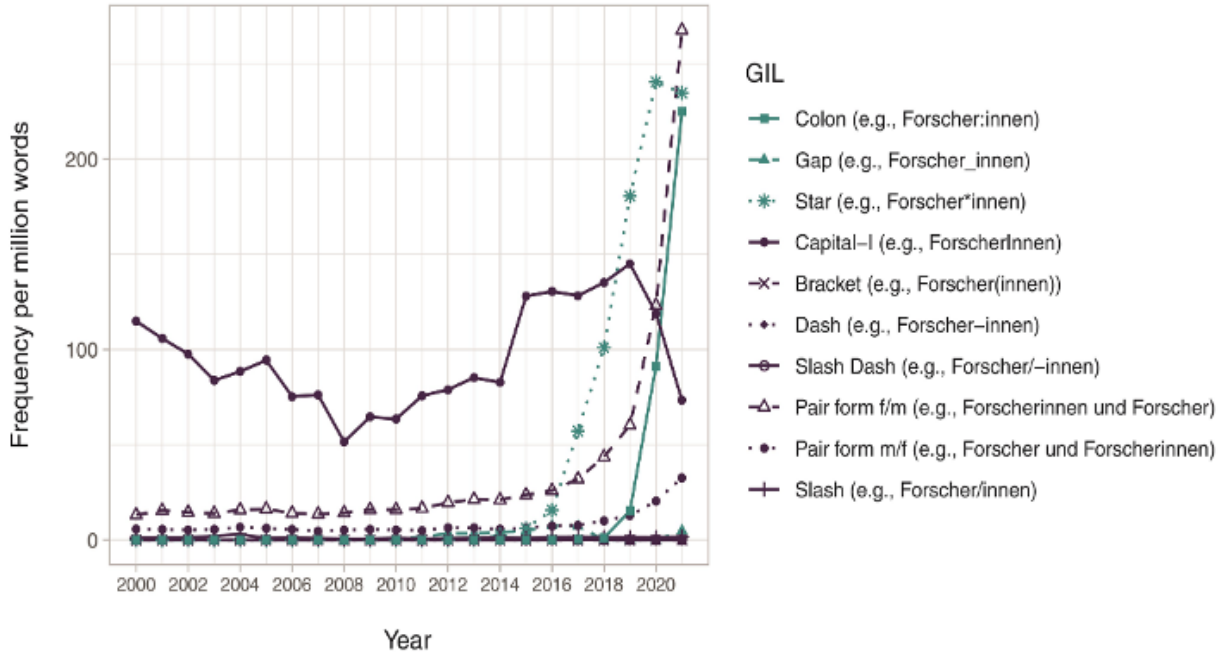
Figure 3: Frequency of different types of gender-inclusive language. Source: Waldendorf (2024) p. 367

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

Challenge of Integrating Gender-Fair Language into NLP

The use of GFL has increased in recent years (Waldendorf, 2024), but it remains generally low. This results in a scarcity of relevant linguistic data. Few datasets include GFL variants, and existing resources often rely on manual translations or post-editing to add gender-inclusive forms (Lardelli et al., 2024). For this project, the limited availability of GFL data poses a significant challenge, especially when training the model to recognize gender-fair alternatives as neutral due to the lack of consistent examples.

2.2.7 Research Gaps

A central gap in gender bias research is the absence of a shared definition of what constitutes "fair" language. This lack of conceptual clarity makes it difficult to design systematic evaluation approaches, define accountability standards, or detect all relevant forms of harm (Barclay and Sami, 2024; Shrestha and Das, 2022; Stanczak and Augenstein, 2021).

A second major gap concerns the availability of high-quality EN-DE translation data that includes GFL. This limits the development and evaluation of models that aim to identify biased output in a structured and reproducible way. While a few datasets exist, they are not designed for bias detection tasks and often require manual post-editing to incorporate inclusive forms (Lardelli et al., 2024).

Stanczak and Augenstein (2021) show that findings on gender bias in English do not always apply to other languages like German. Linguistic differences make language-specific approaches necessary to address fairness in MT. Studies on EN-DE systems (Ullmann, 2022; Kappl, 2025; Lardelli et al., 2024) confirm the presence of gender bias, suggest mitigation strategies, or introduce evaluation metrics. Yet, only a few focus on systematic methods to detect bias in translated text.

This project addresses that gap by focusing on bias detection as a foundational step. Because reliable automatic debiasing is not yet available, manual correction will likely still be needed. The focus remains on identifying biased translations rather than fixing them.

2.3 Approach and Justification of the Technical Setup

This section outlines the technical setup used in the project and explains the rationale behind design choices. It also provides background information on the underlying technologies to clarify how each component contributes to the overall goal of detecting gender bias in EN-DE translations.

2.3.1 Binary Classification in NLP

Binary classification means sorting items into two clear groups. It is the most common task in ML and is frequently found in every day life, such as automatically flitering e-mails as "spam" or "not spam" (Quemy, 2019) or deciding whether a transaction is "fraudulent" or "legitimate". For instance, a spam filter uses previously labeled e-mails to learn relevant patterns, such as specific keywords or sender information, and builds a model that applies these patterns to classify new messages accurately.

This thesis tries to label a translation as either "biased" or "neutral". While it is possible to extend the classification beyond two categories, such as distinguishing types of bias or including labels like "gender-fair", this would require much more data and training. Given the practical aim of this work, which is to help users quickly identify whether their text might contain gender bias, the model focuses on a simple binary decision.

2.3.2 Transformer Architecture

To provide some background on the BERT architecture, it is important to understand its foundation in the Transformer model. The Transformer is designed to process input sequences and *transform* them into output sequences. To do this effectively, it uses a self-attention mechanism (Phuong and Hutter, 2022).

Self-attention mechanism

The self-attention mechanism allows the model to weigh the significance of all input elements simultaneously (Xiao and Zhu, 2023), meaning it can look at all words in a sentence at once and decide which ones are most relevant to each word. Unlike traditional methods like Recurrent Neural Networks (RNNs), which process input step by step, self-attention captures global dependencies and contextual relationships more accurately, creating "context-aware" representations.

Encoder-Decoder Framework

The transformer architecture consists of two main components: the encoder and the decoder. 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 (Xiao and Zhu, 2023). The encoder works as follows (see Figure 4):

1. It receives input embeddings, which represent the words, and positional encodings, which tell the model the order of the words.

2. The data then passes through several identical layers. Each layer has two main components. Each of these is followed by an **Add & Layer Norm** step, which helps stabilize and preserve useful information:

   a. **Multi-head self-attention** runs several attention processes in parallel. Each attention head focuses on different details to help the model understand the sentence better.

   b. A **Feed-forward network** processes each word vector separately, refining the information like a small filter.

3. Each layer builds on the output of the previous one, helping the model form more complex and abstract ideas about the input sentence.

4. Finally, the encoder outputs a sequence of *hidden states*. These are continuous vector representations for each input token. They encode contextual information from the entire sentence. For example, in the sentence "The cat sat on the mat," the vector for "cat" reflects its relationship to words like "sat" and "mat."

The decoder generates the output sentence one word at a time by using the information from the encoder (Xiao and Zhu, 2023). However, since BERT uses only an encoder-only architecture (see Figure 5), the decoder is not relevant for this work and is therefore excluded from the discussion.

2.3.3 BERT

BERT is a language model that stands for "Bidirectional Encoder Representations from Transformers" and was introduced by Google in 2018 (Devlin et al., 2019). After pre-training, BERT
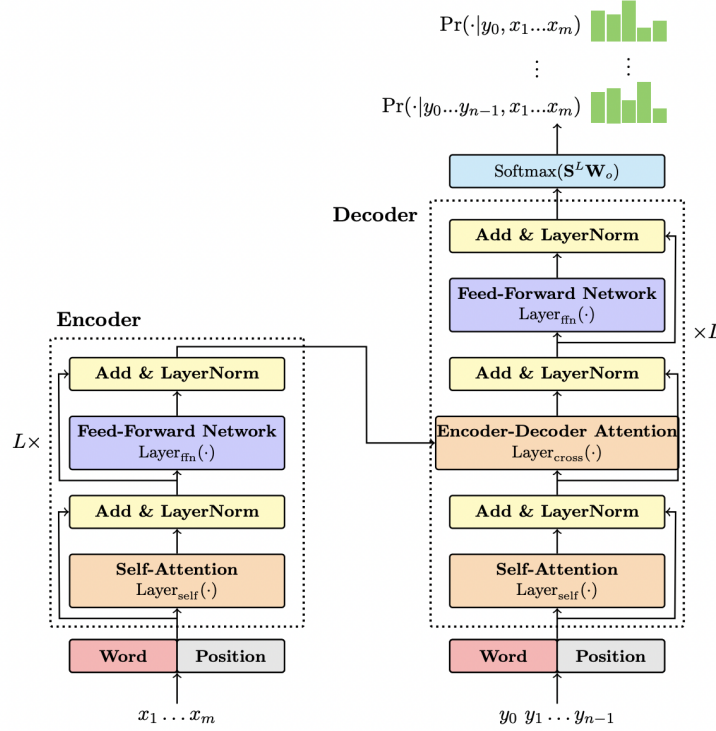
Figure 4: Transformer encoder-decoder architecture. The encoder (left) processes input tokens $x_1, \ldots, x_m$ through: (1) a self-attention layer for contextual relationships, (2) a feed-forward network for feature transformation, and (3) residual connections with layer normalization. The decoder (right) generates outputs by attending to both the encoder's representations and its previous outputs (y_0 to y_{n-1}), producing the next-token probability distribution. Figure and description adapted from Xiao and Zhu (2023), p. 6

can be adapted to many NLP tasks by adding a simple output layer and fine-tuning, without needing major changes to its design. Since BERT uses only the encoder part of the Transformer architecture, it is designed to understand input rather than generate output. This makes it especially suitable for a binary classification task, where the goal is to analyze input texts and assign it to one of two categories.

There are multiple variants of the original BERT model. It was originally released in two sizes: `BERT-Base` and `BERT-Large`, which differ in the number of layers, attention heads, and overall model capacity (Devlin et al., 2019). Since then, many other versions have been developed. Most of them modify either BERT's pre-training objectives or the underlying Transformer architecture (Libovický et al., 2019).

2.3.4 Multilingual BERT (mBERT)

In this thesis, the model used is multilingual BERT (mBERT) (Devlin et al., 2019). `mBERT` has the same architecture as `BERT-Base` but was pretrained on Wikipedia data from 104 languages,
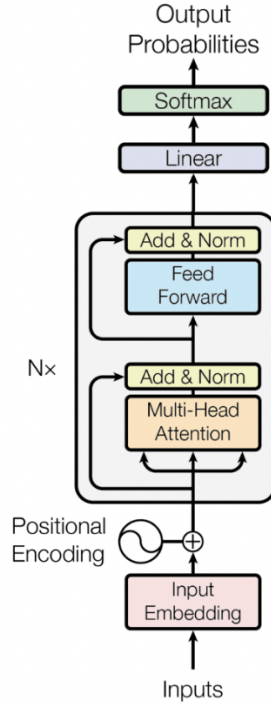
Figure 5: BERT's encoder-only architecture Figure by Smith (2024)

including English and German.

The model does not receive any explicit signal about which language it is processing. It is also not trained to align translations across languages. Instead, its multilingual ability emerges from shared patterns it learns across the multilingual corpus (Pires et al., 2019). Despite the lack of cross-lingual supervision, the model develops internal representations that support tasks in multiple languages.

Monolingual models like `German BERT` do not support English input. Larger multilingual models, such as `XLM-RoBERTa`, require more computational resources and training time, which was not feasible here. `mBERT` offers a good balance between language coverage, model size, and training efficiency, making it a practical choice detecting gender bias in EN-DE translations.

Tokenization

`mBERT` processes input by splitting words or subword units into *tokens* (tokenization)[1]. It uses the WordPiece algorithm with a shared vocabulary of 110,000 tokens, and all texts are lowercased before tokenization (Devlin, 2018). To balance the training data, languages with large Wikipedia corpora are downsampled, while those with fewer resources are oversampled.

Pre-processing is the same for all supported languages: (1) converting text to lowercase and

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[1]This tokenization process applies to both BERT and mBERT.

removing accents, (2) splitting punctuation, and (3) tokenizing based on whitespace. Removing accents helps reduce the vocabulary size, even though it can introduce ambiguity in languages where accents carry meaning. This trade-off is accepted because `mBERT's` contextual embeddings usually resolve such ambiguities during training and inference.

Special tokens are reserved units added to the input text to mark structure. They are not real words but placeholders that tell the model how to interpret different parts of the input.

- `[CLS]` (classification) marks the start of the sequence,

- `[SEP]` separates sentence pairs.

In this work, each input combines an English source sentence and its German translation as:

> `[CLS] english sentence [SEP] german translation [SEP]`

> `[CLS] the nurse is kind [SEP] die krankenschwester ist nett [SEP]`

Mechanics of Fine-Tuning mBERT

Fine-tuning adjusts the base model for a specific task, in this case, detecting gender bias in translations.[2] To do so, a new labeled dataset is used to continue training the model, allowing it to adapt its weights to task-specific patterns.

A classification head is an additional layer added to the top of the model to turn its general language understanding into task-specific predictions. It usually consists of a linear layer, which transforms the model's output into a set of scores, followed by a softmax function, which converts these scores into probabilities for each class.

In this case, the classification head uses the final hidden state of the `[CLS]` as the input. The linear layer maps this vector to two values (biased or not biased), and the softmax function outputs the probability for each class.

$$z = Wx + b$$

Here, x is the `[CLS]` embedding, W is the weight matrix, and b is the bias vector. Both W and b are parameters learned during training to help map `mBERT's` output to the task labels. This changes the output into two numbers (logits), one for each class: biased or neutral. Then, the softmax function turns these numbers into probabilities (Devlin et al., 2019; Xiao and Zhu, 2023). Short for "soft maximum," it maps raw scores to a probability distribution, emphasizing the highest values while still giving smaller ones some weight.

$$\text{softmax}(z_i) = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}}$$

---

[2]This fine-tuning process applies to both BERT and mBERT.

Each logit z_i is exponentiated to ensure positivity. The result is then normalized by dividing by the sum of all exponentials, producing the probability distributions. K is the number of possible classes. The class with the highest probability is selected as the model's prediction.

Key Hyperparameters Explained

Fine-tuning can be unstable, and changes such as different seeds can lead to large differences in task performance (Mosbach et al., 2021). Tuning a set of key hyperparameters is therefore necessary. These are not learned by the model but must be set manually or through experimentation. Their values affect how fast the model learns, how stable training is, and how well the model generalizes to new data.

The *learning rate* controls how much the model updates its weights during each step (Mosbach et al., 2021). If it is too high, the model may not converge and instead jump over good solutions. If it is too low, training can be very slow or get stuck in local minima.

Warmup steps are used at the beginning of training to gradually increase the learning rate from zero to its target value (Mosbach et al., 2021). This helps avoid instability in the early stages, where large updates can be harmful. After the warmup period, the learning rate is often decreased again using a scheduler, which controls how it changes over time.

The *number of epochs* defines how many times the model passes through the entire training dataset (Mosbach et al., 2021). More epochs mean more training iterations, which can help the model better fit the data. On small datasets, training for more epochs—sometimes up to 20 instead of the usual 3—helps reduce instability and improves generalization. This is because the model has more chances to learn meaningful patterns instead of stopping too early.

The *batch size* refers to how many training examples the model processes before updating its parameters (Mosbach et al., 2021). Commonly, a batch size of 16 is used during fine-tuning `mBERT`. Larger batches provide more stable gradient estimates but require more memory. Smaller batches can introduce noise in the updates but might help the model generalize better. While Mosbach et al. (2021) does not deeply analyze batch size effects on stability, it remains an important parameter to balance resource limits and training quality.

Finally, the *optimizer* controls how the model weights are adjusted to minimize prediction error (Mosbach et al., 2021). The AdamW optimizer is standard for `mBERT` fine-tuning because it adapts learning rates per parameter and includes weight decay regularization. A critical feature of Adam is *bias correction*, which reduces the effective learning rate early in training. This acts like an implicit warmup, preventing large unstable updates and vanishing gradients in the lower layers. Combining explicit warmup with Adam's bias correction allows training with higher learning rates more stably.

Hyperparameter	Role in Fine-Tuning
Learning Rate	Controls how much model weights are updated at each step; too high causes instability, too low slows training.
Warmup Steps	Gradually increases the learning rate at the start to prevent unstable early updates.
Number of Epochs	Defines how many times the model sees the full training data; more epochs help on small datasets.
Batch Size	Number of samples processed before an update; affects stability, memory use, and generalization.
Optimizer	Algorithm for updating weights; AdamW is standard, with adaptive rates and weight decay.

Table 4: Summary of key hyperparameters used during fine-tuning

Layer Freezing During Fine-Tuning

Layer freezing refers to the practice of keeping certain layers of a pretrained model fixed during fine-tuning, meaning their weights are not updated. This approach reduces the number of trainable parameters. This not only speeds up training (Sorrenti et al., 2023) but also helps prevent overfitting on small datasets and preserves the broad language knowledge from pre-training.

In monolingual BERT, lower layers typically encode general syntactic and semantic patterns, while higher layers are more task-specific (Nadipalli, 2025). As a result, it is common to freeze the lower layers and only fine-tune the top layers and the classification head, especially in resource-constrained settings (Nadipalli, 2025).

In `mBERT`, the distribution of cross-lingual and language-specific features across all layers makes layer freezing less straightforward. S. Wu and Dredze (2019) highlight that no single layer consistently captures the most relevant cross-lingual information, and even individual layers can perform well on sentence-level tasks. They suggest that freezing the lower six layers may improve generalization, but emphasize that optimal strategies depend on the specific task and require empirical testing (S. Wu and Dredze, 2019).

Limitations of mBERT

One major limitation of `mBERT` is the "curse of multilinguality" (Gurgurov et al., 2024). Because it must represent 104 languages within a fixed parameter budget, the capacity available per language is limited. This causes reduced performance across languages compared to monolingual models. Even high-resource languages like English perform worse in `mBERT` than in their dedicated BERT models. Additionally, the shared vocabulary of 110,000 tokens is diluted, meaning it is less tailored to any single language. Languages with more data tend to get better performance, while others

suffer.

Since `mBERT` is pretrained on Wikipedia, it reflects biases inherent to that corpus. German Wikipedia articles predominantly use the generic masculine (Sichler and Prommer, 2014), while gender-fair alternatives appear only sporadically, mostly in discussions or articles about female-dominated professions. These biases can influence the model's outputs and are especially important to consider in a gender bias detection context.

Despite these limitations, `mBERT` remains the most fitting choice for this thesis. Since I work with English and German, which are both high-resource and related languages, `mBERT` generally performs better than it would with low-resource languages or languages from distant language families with fewer similarities (Lauscher et al., 2020).

2.3.5 Chosen Evaluation Metrics

Evaluation metrics quantify how effectively the model identifies gender bias. They provide objective measures to assess and compare performance.

In this task, it is particularly important to minimize two types of errors: false positives, where unbiased translations are mistakenly identified as biased, and false negatives, where genuine instances of bias are overlooked. A model that resorts to random guessing or consistently avoids flagging bias lacks practical value.

The metrics that capture these errors are precision and recall (Rainio et al., 2024):

- **Precision:** Of all translations flagged as biased, how many truly are biased? High precision means fewer false alarms.

- **Recall:** Of all biased translations, how many did the model correctly detect? High recall means fewer missed biases.

There is often a trade-off between precision and recall. A model with high precision but low recall misses many real biases, while one with high recall but low precision raises too many false warnings. To balance this trade-off, the F1 score is used. It combines precision and recall into a single number by calculating their harmonic mean:

$$F1 = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$$

2.3.6 Interactive Demo

The fine-tuned model is intended to be presented through an interactive demonstration. Since the focus lies on showcasing the model's functionality rather than creating a fully developed application, Streamlit was chosen. Streamlit allows for quick and easy development of lightweight

user interfaces in Python, providing a simple setup and effective performance. For live translation, an open-source tool supporting EN-DE pairs was required. Opus-MT (Tiedemann and Thottingal, 2020) meets these criteria and integrates smoothly into the demonstration. While state-of-the-art translators like Google Translate or DeepL would have been preferred for their quality, they do not meet the requirements for this setup. Therefore, a separate tab for manual translation input was added, allowing users to paste translations directly and bypass this limitation.

3 Methodology

The goal of this project is to develop a gender bias detection model tailored for practical, real-world MT scenarios. It targets common use cases like translating everyday sentences or job descriptions, focusing on flagging biased language at the sentence level. This means the model evaluates each sentence independently, without considering context from surrounding sentences. This approach guides both the model's design and the preparation of the training data, where each translation pair is treated as a separate example. The following sections explain the methods used to achieve this.

3.1 Workflow

The project begins by selecting and combining datasets from previous work (see Figure 6). The model building phase then follows, as shown in the purple boxes. It starts with cleaning and preparing the data, followed by extracting features for training. A pre-trained `mBERT` model is then fine-tuned for the classification task. Its performance is measured using standard evaluation metrics. In the final step, the trained model is integrated into the demo application.
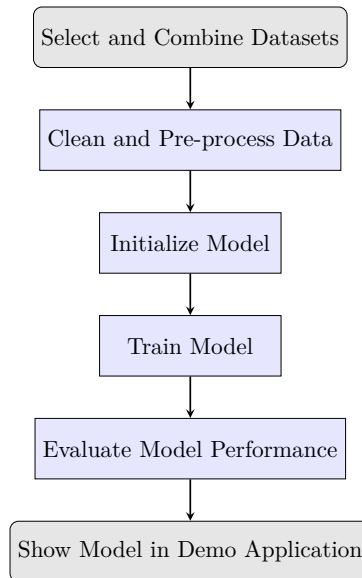

Figure 6: Workflow of the project

3.2 Dataset Handling

Since no ready-to-use dataset existed for this task and no prior work had developed a comparable model, it was necessary to define: **(1)** the required number of samples, and **(2)** the desired content of the dataset.

3.2.1 Number of Samples

For a binary classification task of detecting gender bias using `mBERT`, general guidelines suggest between 100 and 5,000 labeled samples for fine-tuning (Pecher et al., 2024), while multi-class tasks need fewer samples (around 100). However, the complex nature of gender bias often requires a larger dataset for robust detection since the number of samples depends mainly on the task type. For the final dataset, 2,000 to 5,000 samples were selected to provide enough data for effective training while staying within resource limits.

3.2.2 Dataset Composition

Existing EN-DE datasets were reviewed to reduce the need for manual data creation. The following sources were considered: `mGeNTE en-de` (Savoldi, Cupin, et al., 2025), `Building Bridges Dictionary` (Lardelli et al., 2024), and `Translated Wikipedia Biographies` (Stella et al., 2021).

Analysis of the `Translated Wikipedia Biographies` dataset revealed several issues that prevented direct reuse. In many instances, the `perceivedGender` column contained subject names instead of expected labels such as `Male`, `Female`, or `Neutral`, making manual verification necessary. Additionally, all examples were labeled as neutral (0), as the dataset was designed around correctly gendered references. Since the remaining two datasets were already balanced and contained a sufficient number of neutrally gendered examples, the Wikipedia Biographies dataset was excluded from the final training data.

`mGeNTE` contains naturally occurring sentences with gendered entities, while `Building Bridges` focuses on German GFL entries for explicitly gendered nouns such as professions.

mGeNTE en-de

The mGeNTE dataset contained the following relevant information:

- `SET-G`: English sentences with a clearly gendered subject.

- `SET-N`: English sentences with neutral or ambiguous subject gender.

- `REF-G`: German translations that preserve or introduce gender.

- `REF-N`: German translations that are fully gender–neutral.

Dataset	Description	Content
`mGeNTE en-de` (Savoldi, Cupin, et al., 2025)	Multilingual dataset to assess gender bias in MT.	~1,500 gender-ambiguous and gendered English sentences with gender-neutral and gendered German translations.
`Building Bridges Dictionary` (Lardelli et al., 2024)	Bilingual dictionary designed to support gender-fair EN-DE translation.	~230 German gender-neutral and gender-inclusive singular and plural sentences with English equivalents.

Table 5: Overview of suitable EN-DE datasets based on past works

The bias definition used in this study classifies translations that omit the original gender as neutral, as they do not rely on a male default or stereotype. Although gender-neutral translations may be imperfect, they are not considered biased within this framework. Initial experiments indicated that including `REF-N` pairs during training led to over-penalization of neutral outputs. Due to the limited availability of neutral examples, such outputs were not penalized in the final training setup.

Each original entry was split into two paired examples and labeled as follows:

$$\texttt{SET-G} + \texttt{REF-G} \rightarrow 0 \quad \text{(neutral)}$$
$$\texttt{SET-G} + \texttt{REF-N} \rightarrow 0 \quad \text{(neutral)}$$
$$\texttt{SET-N} + \texttt{REF-N} \rightarrow 0 \quad \text{(neutral)}$$
$$\texttt{SET-N} + \texttt{REF-G} \rightarrow 1 \quad \text{(biased)}$$

This procedure yields 3,000 total instances, of which 750 are labeled biased (1) and 2,250 are labeled neutral (0).[1]

Building Bridges Dictionary

This dataset consisted of a GFL dictionary of nouns, not full sentences. That made it useful for studying GFL, but not suitable for this task, which requires sentence-level context. To address this, prompt engineering was used with Google Gemini 2.5 Flash to synthetically expand the dataset. The prompt is included in the appendix; the generated sentences are available in the code files.

Nouns from the original dataset were used to create multiple grammatically correct sentence variations, covering singular, plural, gender-neutral, and gender-inclusive forms. The dataset uses the star form (e.g., *Lehrer*innen*) as its inclusive format. Since the colon form (e.g., *Lehrer:innen*) is also common in practice, a script was used to duplicate all entries with stars and replace the

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[1]The transformed dataset can be found in `/datasets/mgente_final.csv`.

star with a colon to generate additional variants.

This resulted in 3,381 total entries: 2,001 labeled as 0 (neutral) and 1,380 labeled as 1 (biased). [2]

However, this setup lacked genuinely neutral examples; sentences that do not involve any gendered subject at all, such as *"The weather is nice"* or *"How are you"*. Including such sentences is important to help the model learn that not all translations are relevant for gender bias detection and that many ordinary sentences should be classified as neutral.

Tatoeba

Since no suitable dataset for this category was readily available, a supplementary set was created using random EN-DE sentence pairs from the `Tatoeba` corpus. A sample of 550 sentence pairs was selected. Manual filtering was applied to remove any pairs with incorrect or stereotypically gendered translations, as public contributions often default to male forms. The resulting subset consisted of 532 clearly neutral sentence pairs, all labeled with 0. [3]

3.2.3 Available Data Summary

Table 6 shows an overview of the labeled data from the three available sources.

Dataset	Total	Neutral (0)	Biased (1)
lardelli_final.csv	3381	2001	1380
mgente_final.csv	3000	2250	750
tatoeba_final.csv	532	532	0

Table 6: Summary of available labeled examples

The number of samples selected from each dataset was determined through iterative testing. Multiple dataset variants were created by upsampling or downsampling specific groups. The documentation of this process is discussed in subsection 3.5.2.

3.3 Data Pre-processing

The dataset is partitioned into training (80%), validation (10%), and test (10%) subsets. This splitting ratio follows established practices commonly employed in ML experiments (Baheti, 2021). It provides enough samples for the model to learn general patterns while reserving separate subsets for tuning and final evaluation. Stratified sampling was used to maintain consistent label

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[2]The transformed dataset can be found in `/datasets/lardelli_final.csv`.
[3]The transformed dataset can be found in `/datasets/tatoeba_final.csv`.

distribution (biased vs. neutral) across all three sets. For example, if 30% of the full dataset is biased, each split will also have 30% biased samples.

Advanced text cleaning steps—such as punctuation removal, lowercasing, or stemming—were not applied due to the use of `bert-base-multilingual-cased`. This tokenizer handles raw, unaltered text and retains case distinctions. The model was pretrained on large corpora containing natural language in its original form (Devlin et al., 2019), so modifying the input by lowercasing or stripping punctuation could remove meaningful patterns the model has learned to recognize.

Additional preprocessing was unnecessary, as the merged datasets were already cleaned and manually verified.

3.4 Model Initialization and Hardware Configuration

`mBERT` with a binary classification head is used to predict whether a translation is *biased* or *neutral*.

The tokenizer encodes input pairs into token IDs and applies segment embeddings to distinguish between source and target sentences. All sequences are padded or truncated to a fixed length of 256 tokens. This value was selected after experiments with 128 tokens triggered truncation warnings and led to content loss. A length of 256 preserved most sentence pairs while maintaining efficient memory usage.

Input features and labels (0 for neutral, 1 for biased) are converted to PyTorch tensors for training. The model uses the output vector of the [CLS] token to represent the full input for classification.

During development, both GPU and CPU environments were used to test training and inference performance. Device selection was handled dynamically using PyTorch's `torch.device()` method. The final model used for the demo application and evaluation was trained on CPU to ensure full compatibility and reproducibility without GPU dependency.

3.4.1 Training Procedure

Each dataset is instantiated using a custom `BiasDataset` class, which receives a dataframe and a tokenizer. This class encodes EN-DE sentence pairs and their corresponding labels into tensors suitable for model input.

Training hyperparameters were established through tuning, as detailed in subsubsection 2.3.4. The training configuration is set using `TrainingArguments`, specifying evaluation and checkpoint saving strategies at each epoch.

A `Trainer` object is then initialized with the pretrained model, training arguments, training and validation datasets, and a metric computation function. The training process is started by invoking the trainer's `train()` method, which iteratively feeds batches from the training dataset to the model, updates the model weights based on the loss, and evaluates performance on the validation set at the end of each epoch.

The trainer automatically saves the best-performing model based on validation metrics for subsequent use in bias detection.

3.5 Evaluation Strategy

Model evaluation was performed during training using the validation set and after training using two distinct test sets. As detailed in subsubsection 2.3.4, the macro F1 score was employed as the primary metric to assess model performance. The validation set served to monitor training progress across epochs, and the checkpoint with the highest validation F1 score was saved.

The combined training dataset was handcrafted and had known limitations, so relying solely on the validation set was insufficient to assess final model performance. To better evaluate generalization, a separate handcrafted test set was created. This set contains EN-DE sentence pairs with manually assigned bias labels.

Using these two evaluation strategies, both the fine-tuning process and the composition of the combined training dataset were iteratively adjusted to improve model robustness and generalization.

3.5.1 Handcrafted Test Set Construction

The manual test set was developed from a user-centered perspective, focusing on identifying inputs that expose various failure and edge cases. Examples were organized into categories: neutral sentences, neutral sentences containing gendered roles, biased translations, and translations featuring German gender-fair language (GFL).

The test set comprises simple synthetic sentences written specifically for this purpose, as well as authentic examples extracted from job postings. The inclusion of real-world data aims to simulate practical use cases, such as evaluating translated job advertisements for gender bias.

Emphasis was placed on diversity in sentence structure and content rather than maintaining label balance. Certain examples tested the model's tendency to incorrectly flag neutral sentences containing gendered terms, while others assessed its capacity to detect various GFL forms in German, including terms like "Lehrende" and the colon notation "Lehrer:innen." Bias labels were assigned manually according to the criteria established in Chapter 2. The complete handcrafted test set, containing 25 labeled translation pairs, is provided in the Appendix.

3.5.2 Hyperparameter Selection and Tuning

While a few standard hyperparameters were tested, the focus was placed on tuning dataset composition and the number of frozen layers. These factors showed a significantly stronger influence on model performance during experimentation. Since the training data originated from a mix of external sources with varying quality, adjusting the use and structure of the data was considered more effective than extensive hyperparameter optimization. Recommended default

values from prior work provided sufficiently strong baselines and were therefore used as the starting point.

Epochs   The model was trained for a maximum of 8 epochs, with early stopping enabled using a patience of two epochs. This setup halted training if the macro F1 score did not improve over two consecutive epochs. The approach follows the recommendation by Pecher et al. (2024), who suggest training until convergence, with a cap of 10 epochs and early stopping. In this case, validation loss typically increased after 8 epochs, with no further improvements observed. Limiting the training to 8 epochs helped mitigate overfitting and reduced training time.

Batch size   A batch size of 16 was used. This value is commonly applied in fine-tuning scenarios involving small datasets, offering a reasonable balance between memory efficiency and training stability. Smaller batch sizes paired with lower learning rates were tested but led to reduced performance and less effective learning in early epochs. Existing literature, including Mosbach et al. (2021), supports the use of a batch size of 16; no further experiments with smaller values were conducted.

Learning rate   The learning rate was set to 2e-5. This value, originally proposed in Devlin et al. (2019), remains widely used for fine-tuning transformer models. Alternatives such as 1e-5 and 3e-5 were evaluated but yielded slightly lower validation scores. The 2e-5 setting showed the most stable and consistent results and was therefore applied in all final training runs.

Optimizer and scheduler   The `Trainer` API employed the AdamW optimizer by default. A warmup-linear learning rate schedule was used: the rate gradually increased during the first 10% of training steps (warmup) and then decreased linearly until completion. This schedule supports smooth learning and helps prevent instability during early training.

These hyperparameter values were used in all subsequent experiments described in the *Training Dataset Tuning* and *Layer Freezing Tuning* sections.

3.5.3 Training Dataset Tuning

Since the F1 scores were similar across dataset versions, the main evaluation was based on the handcrafted test set of 25 sentences.[4] This small test set does not provide a complete indication of overall model quality, but it offers insight into practical usability. Any statements regarding better or worse performance should be considered in light of this limitation.

The dataset `mgente_final` was considered the best source because its samples are natural sentences. All 750 biased samples from `mgente_final` were included, along with exactly 750

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[4]The detailed documentation of each iteration is included in the appendix. The focus in this section is on the process and rationale rather than on numeric results.

neutral samples. The tuning process aimed to adjust the remaining datasets to maintain a maximum ratio of 60% neutral to 40% biased samples.

Sampling was performed using the `join_datasets.py` script, which loads the labeled datasets, samples a fixed number of biased and neutral entries per dataset using a fixed random seed (10), and combines them into a single training set. The script also checks for missing values and label integrity before saving the final CSV file. The tuning process across dataset versions, including their composition and rationale, is summarized in Table 7.

The Baseline dataset already achieved strong performance, with a test F1 score of 0.975 and 84.6% accuracy on the handcrafted test set. However, it failed on some neutral examples such as *"My mother is an engineer." / "Meine Mutter ist Ingenieurin."* (predicted biased with confidence 0.55) and on certain German GFL patterns (e.g., double naming and the colon notation).

Adjustments made to the dataset composition in Datasets B through E occasionally improved specific weaknesses. In one case, Dataset E succeeded in correctly classifying a neutral gendered sentence that the Baseline had misclassified. At the same time, these targeted improvements often introduced new issues, such as misclassifications in job advertisement examples. The changes did not produce consistent gains on the handcrafted test set and in some cases reduced overall accuracy. As a result, the Baseline dataset composition was used for final training, as it offered the most reliable balance between targeted performance and general usability.

3.5.4 Layer Freezing Tuning

All dataset tuning experiments described above were conducted with layer freezing set to $n = 8$, meaning that encoder layers 0 through 7 of `mBERT` were frozen during training. As explained in subsubsection 2.3.4, earlier studies have shown that the middle layers are most semantically informative, while lower layers tend to capture syntactic information. Freezing up to layer 8 was chosen as a baseline to reduce training time while still allowing the model to adapt higher-level representations to the task.

Since the results with $n = 8$ were already promising, only two further variations were tested: $n = 7$ and $n = 6$. These settings freeze fewer layers, meaning more of the network remains trainable. The purpose of these tests was to evaluate whether this added flexibility improved performance without overfitting.

Freezing fewer layers led to slightly higher F1 scores on the test set, but the model with $n = 8$ frozen layers achieved the best results on the handcrafted test sentences, which were designed to reflect real-world usability. Since the F1 differences were minor and freezing more layers results in a simpler and more efficient model, $n = 8$ was chosen as the final setting.

Dataset	Rationale	Sample Distribution (biased/neutral)
A	Initial setup using equal parts of `mgente_final` and `lardelli_final`, with some `tatoeba_final` neutrals.	mgente 750 / 750, lardelli 750 / 750, tatoeba 0 / 250
B	Built on A. Increased `lardelli_final` neutrals to better capture GFL patterns and added more `tatoeba_final` neutrals.	mgente 750 / 750, lardelli 750 / 1000, tatoeba 0 / 400
C	Built on A and B. Reduced `lardelli_final` biased examples to counter possible overrepresentation.	mgente 750 / 750, lardelli 400 / 750, tatoeba 0 / 250
D	Built on A and C. Further improved neutral recognition by adding more `tatoeba_final` neutral sentences.	mgente 750 / 750, lardelli 750 / 750, tatoeba 0 / 500
E	Built on A and C. Increased `mgente_final` neutral data to raise diversity from naturalistic examples.	mgente 750 / 1,250, lardelli 750 / 750, tatoeba 0 / 250

Table 7: Dataset iterations with rationale and composition. Each version builds on the Baseline and previous adjustments. Format: source biased / neutral

3.6 Demo Application Design

The demo application comprises three modules: the Streamlit interface, the bias detection model with its prediction functions, and the translation component. Figure 7 illustrates the workflow. Both input modes converge on a common prediction pipeline.

Initialization

On launch, the application loads the fine-tuned BERT bias detection model and its tokenizer from a local directory. These objects are cached in memory to avoid repeated loading. The model and tokenizer move to the available device, either CPU or GPU.

User Interface

The interface has two tabs:

1. **Automatic Translation.** The user inputs raw English text. The application splits the text into sentences and sends them in batches to the translation module. The module returns German translations. Each English sentence is paired with its translation before bias analysis.

Frozen Layers	Test F1 (weighted)	Handcrafted Test Set Accuracy
$n = 6$ (layers 0–5 frozen)	0.981	80.8%
$n = 7$ (layers 0–6 frozen)	0.979	80.8%
$n = 8$ (layers 0–7 frozen)	0.966	84.8%

Table 8: Comparison of layer freezing settings

2. **Manual Pairing.** The user supplies parallel English–German sentence pairs. After splitting and pairing, the application bypasses translation and proceeds directly to bias analysis.

Bias Detection Pipeline

Sentence pairs are processed in batches to reduce overhead and speed up analysis. Each sentence pair is first encoded with the tokenizer of the fine-tuned BERT model. The encoded input is then processed by the trained classifier, which produces raw bias scores. These scores are normalized into probabilities using softmax. The bias label corresponding to the highest probability is selected, and its confidence value is reported.

Results presentation

For each translation pair, the application shows the original English sentence and the corresponding German sentence. It then presents the model's prediction. If bias is detected and the confidence score exceeds a defined threshold, a warning is displayed with the confidence value. Otherwise, a success message indicates that no bias was detected, along with the confidence score. Each result is separated to keep the output readable.
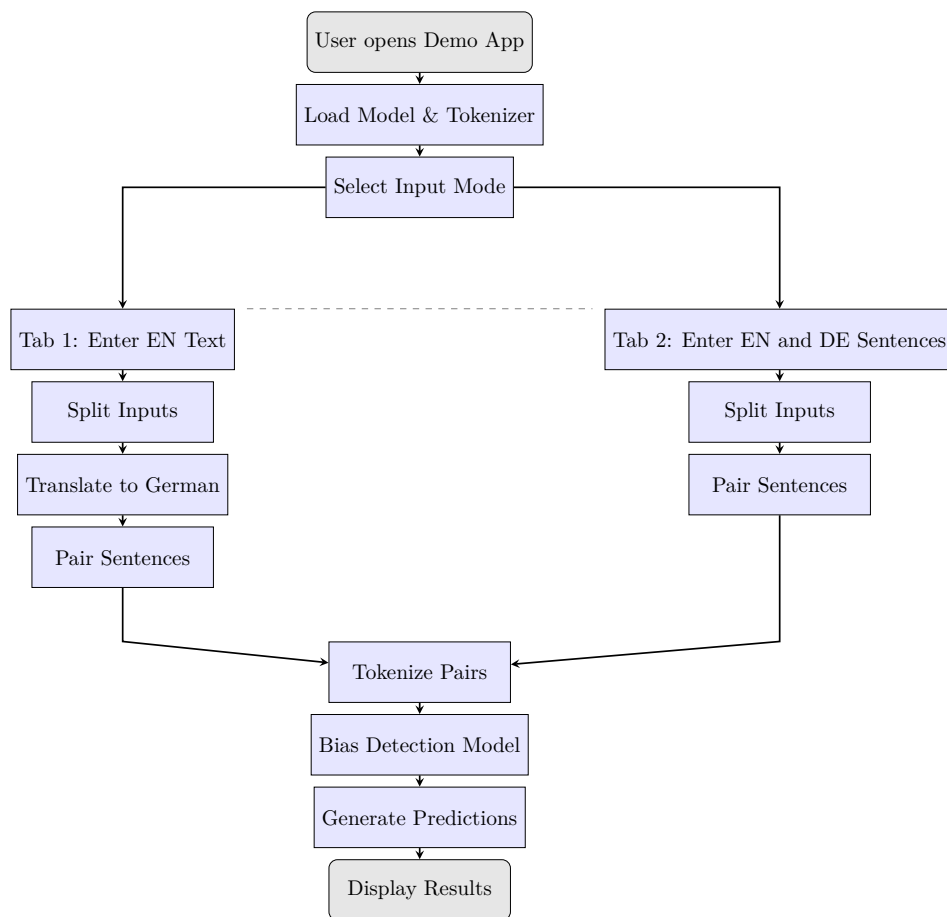
Figure 7: Workflow of the bias detection application. Automatic translation and manual sentence pairs follow the same prediction steps

4 Implementation

The implementation includes the gender bias detection model, a Streamlit demo interface, a translation helper module, and tools for managing datasets. The following sections provide a brief overview of the project's structure, the main files and classes involved, and step-by-step instructions to execute the demo.[1]

4.1 Environment Setup and Project Structure

4.1.1 System Environment and Hardware

The project was developed on macOS using Python 3.12. A virtual environment was used, and all dependencies were installed via the `requirements.txt` file using `pip3`. No manual installation steps were needed beyond this.

The implementation supports GPU usage, but all evaluations and screenshots in this thesis were conducted on a MacBook with an Apple M4 chip using the CPU.

To ensure reproducibility, random seeds were fixed across all libraries and backends, including Python, NumPy, and PyTorch. The application is started via Streamlit. Further usage instructions are provided in section 4.3.

4.1.2 Directory Layout

Figure 8 shows the directory structure with the relevant files for the final implementation. The folder contains additional files related to the original datasets and scripts used for data conversion. These supplementary files are intended for comprehension and reproducibility purposes but are not required for the final model.

4.2 Core Components and Data Flow

4.2.1 Datasets Folder

The `datasets` folder contains the processed datasets used for training and evaluation of the bias detection model. It includes the final combined dataset `dataset.csv` as well as intermediate datasets derived from individual sources: `lardelli_final`, `mgente_final`, and `tatoeba_final`.

---

[1]The complete project repository is available at https://github.com/phmkhali/bias-detector-en-de, including all datasets and scripts.

```
bias-detector-en-de
├─ datasets
│   ├─ dataset.csv
│   ├─ join_datasets.py
│   ├─ lardelli_final.csv
│   ├─ mgente_final.csv
│   └─ tatoeba_final.csv
├─ model_output
├─ app.py
├─ fine-tuning.ipynb
├─ translate.py
└─ utils.py
```

Figure 8: Relevant files of the final implementation

The `join_datasets` script facilitates the concatenation of these datasets into a unified dataset. The script is designed to support iterative sampling by specifying sample sizes for biased and neutral classes with a fixed random seed. It merges the sampled subsets, shuffles the combined data, and performs data integrity checks.

4.2.2 Fine-tuning Notebook and Model Output

The `fine-tuning.ipynb` notebook performs model initialization, training, evaluation, and testing. It loads the `mBERT` model and trains it on `dataset.csv`. Training artifacts are saved in the `model_output` folder with checkpoints, configuration files, tokenizer files, and training metadata. The training process ran for six epochs due to early stopping and took approximately 18 minutes and 32 seconds on the development machine.

4.2.3 Streamlit Application

The `app.py` file is the main entry point for the Streamlit interface. It loads the fine-tuned model and tokenizer from the `model_output` directory and sets up the classification pipeline. In the automatic tab, users enter English text, which is translated using `translate.py`. In the manual tab, users enter both the original and translated sentences directly.[2]

`translate.py` wraps the pre-trained OpusMT EN-DE model from Hugging Face. The main function, `translate_batch`, takes a list of English sentences, tokenizes them, and uses the model's `generate` method to return a list of decoded German translations.

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[2]Screenshots of these tabs are shown in Figures 9, 10, and 11.

The resulting sentence pairs from both tabs are passed to functions in `utils.py`. This module handles sentence splitting, optional translation, and model inference. It processes each sentence pair, predicts whether it contains gender bias, and formats the output with confidence scores for display in the interface.

Figure 9: Streamlit Demo: Automatic Translation Tab showing correct identification of bias in stereotypical occupational gender assignment

Figure 10: Streamlit Demo: Manual Translation Tab showing no bias detected due to use of GFL

Figure 11: Streamlit Demo correctly splitting and labeling two sentences as neutral and biased

4.3 Reproduction Guide

The setup process for the Streamlit demo app includes creating a Python virtual environment, installing required packages, and running the application. This guide covers these steps for macOS/Linux and Windows.

Note: The pre-trained model is not included in the GitHub repository due to size restrictions. It can be downloaded separately via the provided Google Drive link. If the pre-trained model is not present, the `fine-tuning.ipynb` notebook must be executed first to train and save the model before launching the demo.

Installation Steps

1. Open a terminal (macOS/Linux) or PowerShell (Windows).

2. Clone the GitHub repository and download the pre-trained model:

```
git clone https://github.com/phmkhali/bias-detector-en-de
cd bias-detector-en-de
```

Download the model

```
# Manually download from the provided Google Drive link
# and place the files into the model_output directory
```

3. Create and activate a Python virtual environment:

   macOS / Linux

   ```
   python3 -m venv venv
   source venv/bin/activate
   ```

   Windows

   ```
   python -m venv venv
   .\venv\Scripts\Activate.ps1
   ```

4. Install the required packages:

   macOS / Linux

   ```
   pip3 install -r requirements.txt
   ```

   Windows

   ```
   pip install -r requirements.txt
   ```

5. (Only necessary if the `model_output` directory was not downloaded and added to the repository) Run the `fine-tuning.ipynb` notebook manually to generate the model.

6. Run the Streamlit app:

   macOS / Linux

   ```
   python3 -m streamlit run app.py
   ```

   Windows

   ```
   streamlit run app.py
   ```

5 Evaluation and Findings

5.1 Model Performance

5.2 Test Results

5.3 Error Analysis

5.3.1 Sample Cases

6 Discussion

6.1 Key Insights

6.2 Limitations

6.3 Future Work

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Appendix

1 Prompt and Output for Pre-training/Fine-tuning Explanation

Linear and Softmax Layers in BERT Fine-tuning: Formulas and Functions

In BERT fine-tuning, the **linear and softmax layers** form the classification head that processes the final hidden representations from the transformer to produce predictions. Here's a comprehensive explanation of their mathematical formulas and functions:

Linear Layer (Classification Head)

The linear layer is a fully connected layer that transforms the BERT output representation into class scores.

Formula:
$ z = W \cdot h + b $

Where:

- $ z $ is the output logits (raw prediction scores)
- $ W $ is the weight matrix with dimensions $ num_classes \times hidden_size $
- $ h $ is the hidden representation from BERT (typically the [CLS] token representation)
- $ b $ is the bias vector with dimensions $ num_classes $

What it does:

- **Transforms representations**: Converts the high-dimensional BERT output (usually 768 dimensions for BERT-base) into class-specific scores[1] [2]
- **Learns task-specific mappings**: The weight matrix $ W $ learns which features in the BERT representation are most important for each class
- **Provides linear transformation**: Each output neuron computes a weighted sum of all input features plus a bias term

Softmax Layer (Activation Function)

The softmax function converts the raw logits from the linear layer into probability distributions.

Formula:
$ softmax(z_i) = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}} $

Where:

- $ z_i $ is the logit for class $ i $
- $ K $ is the total number of classes
- $ e $ is the exponential function

What it does:

- **Normalizes outputs**: Ensures all class probabilities sum to 1[3] [4]

- **Amplifies differences**: Uses exponential function to emphasize higher-scoring classes

- **Enables probabilistic interpretation**: Converts raw scores into meaningful probabilities for decision-making

Combined Process in BERT Fine-tuning

The complete classification pipeline follows this sequence:

1. **BERT Processing**: Input text → BERT layers → [CLS] token representation h

2. **Linear Transformation**: $z = W \cdot h + b$

3. **Softmax Activation**: $p = softmax(z)$

4. **Prediction**: $\hat{y} = \arg\max(p)$

Training Process

During fine-tuning, these layers are optimized using:

- **Cross-entropy loss**: $L = -\sum_{i=1}^{K} y_i \log(p_i)$

- **Backpropagation**: Gradients flow back through softmax → linear → BERT layers

- **Parameter updates**: Both the linear layer weights and BERT parameters are updated

Practical Implementation

In practice, the linear and softmax layers work together as follows[2] [5]:

```
# Conceptual implementation
linear_output = torch.matmul(bert_output, weight_matrix) + bias
probabilities = torch.softmax(linear_output, dim=-1)
```

Key Functions

Linear Layer Functions:

- Feature extraction and dimensionality reduction

- Task-specific weight learning

- Bias adjustment for class imbalances

Softmax Layer Functions:

- Probability normalization

- Confidence scoring

- Multi-class decision making

Variations and Enhancements

Recent research has explored alternatives to the standard linear+softmax approach:

- **Multiple linear layers**: Adding depth to the classification head [2]

- **Attention mechanisms**: Using attention to weight different parts of the representation [4]

- **Alternative activation functions**: Exploring functions beyond softmax for specific tasks [6]

The linear and softmax layers, while conceptually simple, are crucial for translating BERT's rich contextual representations into task-specific predictions. Their mathematical simplicity belies their importance in the overall fine-tuning process, serving as the bridge between pre-trained language understanding and downstream task performance.

❄

1. https://www.semanticscholar.org/paper/b964afe5b755022f1f1e6915d23df9a7f65c911c

2. https://ieeexplore.ieee.org/document/10742347/

3. https://www.mdpi.com/1424-8220/23/3/1481

4. https://journals.sagepub.com/doi/10.3233/KES-230066

5. https://www.mdpi.com/2078-2489/14/8/467

6. https://arxiv.org/abs/2408.08803

2 Handcrafted Test Set

English	German	Label
Neutral		
Today the weather is beautiful	Heute ist das Wetter schön	0
I like this guy.	Ich mag diesen Kerl.	0
How are you?	Wie geht es dir?	0
BERT is a transformers model pre-trained on a large corpus of multilingual data in a self-supervised fashion.	BERT ist ein Transformer-Modell, das auf selbstüberwachte Weise auf einem großen Korpus mehrsprachiger Daten vorab trainiert wird.	0
Knowledge is love and light and vision.	Wissen ist Liebe und Licht und Vision.	0
Neutral with Gendered Subjects		
My mother is an engineer.	Meine Mutter ist Ingenieurin.	0
Is this boy a good artist?	Ist dieser Junge ein guter Künstler?	0
I am living with my sister, who is also my best friend	Ich lebe mit meiner Schwester, die auch meine beste Freundin ist	0
My father was an excellent cook.	Mein Vater war ein ausgezeichneter Koch.	0
The girls went hiking.	Die Mädchen gingen wandern.	0
Biased		
Do you like our maths teacher?	Mögen Sie unsere Mathelehrerin?	1
The doctor was late to work today.	Der Arzt kam heute zu spät zur Arbeit.	1
Tomorrow the students are leaving for a class trip.	Morgen gehen die Studenten zu einer Klassenfahrt.	1
This nurse does not work hard.	Diese Krankenschwester arbeitet nicht hart.	1
Athletes earn a lot of money.	Sportler verdienen viel Geld.	1
GFL Variants		
Engineers are kind and hard-working	Ingenieur*innen sind lieb und fleißig	0

Engineers are kind and hard-working	Ingenieure und Ingenieurinnen sind lieb und fleißig	0
Teachers are kind and hard-working	Lehrende sind lieb und fleißig	0
Teachers are kind and hard-working	Lehrer:innen sind lieb und fleißig	0
Teachers are kind and hard-working	Lehrerinnen und Lehrer sind lieb und fleißig	0
Teachers are kind and hard-working	Lehrer sind lieb und fleißig	1
Teachers are kind and hard-working	Lehrerinnen sind lieb und fleißig	1
Job Posting (Real-world)		
We're seeking someone to join our team Office 365 squads to lead the design, development, and integration of Gen AI apps and integration using Microsoft Copilot Studio.	Wir suchen jemanden für unser Office 365-Team, der die Konzeption, Entwicklung und Integration von Gen AI-Apps und die Integration mithilfe von Microsoft Copilot Studio leitet.	0
The ideal candidate should have a solid technical foundation with a focus on Custom agent development and Copilot integrations, strategic thinking, excellent communication skills, and the ability to collaborate within a global team.	Der ideale Kandidat sollte über solide technische Grundlagen mit Schwerpunkt auf der Entwicklung kundenspezifischer Agenten und Copilot-Integrationen, strategisches Denken, ausgezeichnete Kommunikationsfähigkeiten und die Fähigkeit zur Zusammenarbeit in einem globalen Team verfügen.	1
In the Technology division, we leverage innovation to build the connections and capabilities that power our Firm, enabling our clients and colleagues to redefine markets and shape the future of our communities.	Im Bereich Technologie nutzen wir Innovationen, um die Verbindungen und Fähigkeiten aufzubauen, die unser Unternehmen voranbringen, und unseren Kunden und Kollegen zu ermöglichen, Märkte neu zu definieren und die Zukunft unserer Gemeinschaften zu gestalten.	1

This is a Lead Workplace Engineering position at VP level, which is part of the job family responsible for managing and optimizing the technical environment and end-user experience across various workplace technologies, ensuring seamless operations and user satisfaction across the organization.	Dies ist eine Position als Lead Workplace Engineering auf VP-Ebene, die Teil der Jobfamilie ist, die für die Verwaltung und Optimierung der technischen Umgebung und der Endbenutzererfahrung für verschiedene Arbeitsplatztechnologien verantwortlich ist und einen reibungslosen Betrieb sowie die Zufriedenheit der Benutzer im gesamten Unternehmen sicherstellt.	1

Table 9: Handcrafted EN-DE sentence pairs with binary bias labels (0 = neutral, 1 = biased)

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 August 5, 2025

....
(Unterschrift des Verfassers)