# Gender bias in MT from Basque into Spanish: the case of gender stereotypical adjectives and occupations

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**Abstract**

With the rise of artificial intelligence, the use of machine translation (MT) has become commonplace. However, concern has been voiced with regard to MT output, from the perspective of both the quality and a range of biases that are evident in texts translated using this technology. In this study, we focus on the phenomenon of gender bias, specifically in the case of translation from languages that have no explicit grammatical gender, such as Basque, to languages that do, such as Spanish.

In the study, we collected samples from three corpora created from texts drawn from different fields (literature, science, and journalism) and examined the translations proposed by an MT system (Elia) with regard to use of stereotypical masculine and feminine adjectives and occupations. Our findings suggest that when no explicit gender is given in Basque, the MT system primarily selects the masculine option in Spanish. Nevertheless, in certain occupations, we observed that the use of certain translation methods can contribute to producing less stereotypical target texts.

## 1 Introduction

Basque-language machine translation software was first developed in the early years of the twenty-first century. Although there are now different MT tools working with Basque, only three were designed specifically for that language: Itzuli (cf. Eusko Jaurlaritza), Batua (cf. Vicomtech) and Elia (cf. Elia). All three are founded on neural networks and are the subject of constant enhancement.

From the outset, there have been concerns about the quality of the results offered by these tools. Amongst the main issues that trouble the research community are those related to racism, ageism and gender bias (cf. Prates et al. 2020; Savoldi et al. 2021; Corral/Saralegi 2022). This article will focus on gender bias and set out the main results and conclusions of a collaborative research project conducted by Elhuyar (cf. Elhuyar) and the TRALIMA/ITZULIK research group from the University of the Basque Country (UPV/EHU).

As the Academy of the Basque Language notes, with the sole exception of the verb form *hika*[1], Basque does not specify gender at a grammatical level (cf. Euskaltzaindia 1991: 36). While there are separate words to distinguish between *senar* 'husband' and *emazte* 'wife', the distinction is lexical and not morphological (cf. Euskaltzaindia 2021). Exceptions to this rule include morphological changes that differentiate gender, such as *lehengusu* 'male cousin'/*lehengusina* 'female cousin' and *alargun* 'widower'/*alarguntsa* 'widow'. However, it is important to note that these are specific cases; moreover, they are only used in specific dialects. By contrast, if we look at the general functioning of Romance languages, we see that grammatical gender is marked by the noun, with other elements such as pronouns and adjectives agreeing with it. Nouns are classified according to their gender, which can be masculine or feminine. The gender designated to inanimate nouns is arbitrary, whereas in the case of animate nouns, gender designation is determined by sex (cf. RAE 2010).

The research questions underpinning the analysis presented in this article are as follows:

- What happens when an MT tool translates a text from a language that has only lexical gender (e. g. Basque) into a language that also has a morphological gender system (e. g. Spanish)?
- Can gender bias be perceived in the result produced by the MT tool?

## 2 State of the art

As several academic publications have shown, the issue of bias, and more specifically gender bias, in MT tools is a cause for concern in the research community (cf. Stanovsky et al. 2019; Prates et al. 2020; Hovy et al. 2020; Savoldi et al. 2021; Ariño-Bizarro/Ibarretxe-Antuñano 2024; Monzó-Nebot/Tasa-Fuster 2024, to mention but a few). However, as Lardelli/Gromann (2022) have noted, the field of gender-fair machine translation is a relatively new one.

Many studies use synthetic data or challenge sets (i. e. corpora consisting of sentences created *ad hoc*) to identify gender bias. The advantages and disadvantages of this type of data are explained by Savoldi et al. (2021): "In this way, they can be used to quantify bias related to stereotyping and under-representation in a controlled environment. However, since they consist of a limited variety of synthetic gender-related phenomena, they hardly address the variety of challenges posed by real-world language and are relatively easy to overfit". For their evaluation of gender bias in MT, Stanovsky et al. (2019) created a challenge set and their analysis of six MT systems revealed significant gender bias in all target languages analysed. The texts were translated from English into eight languages with grammatical gender.

Prates et al. (2020) decided to focus on Google Translate, analysing the impact of gender bias in MT from twelve gender-neutral languages into English. The study observed a strong tendency to employ the masculine gender, particularly in stereotypically male occupations such as STEM, thereby perpetuating gender biases. For instance, the system employed feminine pronouns for nurses and masculine pronouns for engineers. This bias was observed not only in occupations but also in certain adjectives. The authors emphasised the significance of training

[1] The informal verb-form of address in Basque, in which the addressee's gender needs to be marked in the verb: *Emango diat liburua* 'I will give you (male) the book' or *Emango dinat liburua* 'I will give you (female) the book'.

data when designing MT systems, noting that while models cannot be trained with unbiased texts due to their scarcity, efforts must be made to eliminate bias from the system following an initial training phase.

Furthermore, the perpetuation of biases has been observed not only in MT outputs, but also in sentences translated with a generative pretrained transformer (GPT). An experiment conducted by Vanmassenhove (2024) with ChatGPT "in an English-Italian translation setting showed how GPT models perpetuate biases even when explicitly prompted to provide alternative translation. Surprisingly, prompting for gender alternatives often even led to additional biases in the model's outputs, highlighting the need for further research and development in this area" (2024: 244f.).

However, in the field of MT gender bias only a limited number of studies have been conducted involving the Basque language. Noteworthy exceptions include the research of Salaberria et al. (2021), Corral/Saralegi (2022), and Gete/Etchegoyhen (2024). The first study, which analyses the Basque-to-Spanish and Spanish-to-Basque translations produced by three commercial MT systems, concludes that they all exhibit gender bias. The goal of the second study was to improve the results of MT systems in relation to gender bias and the outcomes show mitigation of this aspect. Gete/Etchegoyhen (2024) used non-informative context in Basque to Spanish translations to try to mitigate gender bias; overall, however, they found the use of context to be detrimental.

The aforementioned studies related to Basque were all conducted from the perspective of IT technicians. As García González (2024: 178) observes, "[…] research on and development of MT systems has been mostly carried out without considering the possible contributions of translators and translation researchers to the topic". The purpose of the collaboration between Elhuyar and TRALIMA/ITZULIK has been to analyse the Basque-to-Spanish translations of occupations and adjectives generated by the Elia MT tool (cf. Elia) in real texts, from a translational and linguistic perspective.

## 3 Methodology

For our study, we selected Elia, an AI-based tool that has been providing online services since 2019[2]. The Basque source texts (STs) were taken from a digital monolingual corpus called Dabilena[3] (cf. Dabilena), compiled by Elhuyar in 2021 using real texts from different domains. Three types of texts were chosen – literature[4] (15 million words), news items[5] (61 million

[2] Between 2019 and early 2021, the tool was known as Itzultzailea.eus. In 2021, it was renamed Elia.

[3] This corpus contains 300 million words.

[4] Basque literature from 1983 onwards and the Basque translations of the classics (cf. EHU).

[5] News from Berria (cf. Berria) (online and paper version).

words) and scientific texts[6] (7 million words) – to determine where there are differences between them.[7]

The study focused on the lexical level and the first step was to create two lists of gender-stereotyped adjectives and occupations. The stereotypical adjectives were selected on the basis of work carried out on Elhuyar dictionaries (cf. Sagarzazu 2022) and other studies of the use of non-sexist language in Basque (cf. Barquín 2008; Begira 2016). The resulting list (see Table 1) contained 56 adjectives, 29 related to women and 27 relating to men.

| | |
|---|---|
| Stereotypical female adjectives | *adeitsu* 'polite', *ahul* 'weak', *amatiar* 'motherly', *atsegin* 'nice', *bare* 'quiet', *bihozbera* 'merciful', *biktima* 'victimlike', *delikatu* 'delicate', *eder* 'beautiful', *esaneko* 'obedient', *eztitsu* 'loving', *fin* 'diligent', *hunkibera* 'emotional', *irrazional* 'irrational', *limurtzaile* 'seductive', *lirain* 'slender', *maitekor* 'tender', *makal* 'frail', *martir* 'martyrlike', *mendeko* 'servantly', *negarti* 'given to crying', *otzan* 'meek', *pertxenta* 'graceful', *polit* 'pretty', *sakrifikatu* 'self-sacrificing', *seduktore* 'seductive', *sentibera* 'sensitive', *sentikor* 'touchy', *zaintzaile* 'caring' |
| Stereotypical male adjectives | *adoretsu* 'audacious', *agresibo* 'aggressive', *ahobero* 'boastful', *anbiziotsu* 'ambitious', *andrezale* 'womanising', *ausart* 'brave', *baldar* 'dull', *bortitz* 'fierce', *burujabe* 'independent', *erasokor* 'assailing', *erasotzaile* 'attacking', *gihartsu* 'muscular', *gonazale* 'skirt-chasing', *harro* 'proud', *harroputz* 'arrogant', *heroi* 'heroic', *hornitzaile* 'providing', *indartsu* 'strong', *latz* 'unkind', *lehiakor* 'competitive', *menderatzaile* 'conquering', *mozkor* 'drunkardly', *oldarkor* 'impulsive', *trakets* 'rough', *trebe* 'competent', *zapaltzaile* 'oppressive', *zarpail* 'rude' |

**Table 1: List of adjectives considered as female and male used in the study**

To identify occupation-related stereotypes, we consulted a list of the most common occupations among men and women published in the Spanish press in March 2023 (cf. Sánchez et al. 2023), based on official data and statistics. Given the large number of results, we decided to choose only those with the most examples in Dabilena. The result was a list (see Table 2) of 51 occupations, 35 typically male and 16 typically female (the imbalance between the two genders is striking, with 69% of occupations categorised as male and only 31% as female).

[6] Texts from the website of Zientzia.

[7] Due to space limitations, it is not possible to discuss this issue at greater length here. However, in both absolute and proportional terms, we identified no notable differences between literary, journalistic and scientific texts in the translation of genderless units. The main result is that in all cases the most frequent option given by Elia is the masculine.

| | |
|---|---|
| Stereotypical female occupations | *zerbitzari* 'waiter/waitress', *dantzari* 'dancer', *idazkari* 'secretary', *hezitzaile* 'educator', *zaintzaile* 'caregiver', *kutxazain* 'cashier', *ile-apaintzaile* 'hairdresser', *garbitzaile* 'cleaner', *erizain* 'nurse', *saltzaile* 'salesperson', *irakasle* 'teacher', *itzultzaile* 'translator', *diseinatzaile* 'designer', *farmazialari* 'pharmacist', *aurkezle* 'presenter', *psikologo* 'psychologist' |
| Stereotypical male occupations | *zuzendari* 'principal/director', *idazle* 'writer', *epaile* 'judge', *musikari* 'musician', *mediku* 'doctor', *kazetari* 'journalist', *teknikari* 'technician', *politikari* 'politician', *abokatu* 'lawyer', *gidari* 'driver', *zurgin* 'carpenter', *artzain* 'shepherd', *enpresari* 'businessman/businesswoman', *funtzionario* 'civil servant', *arkitekto* 'architect', *argazkilari* 'photographer', *ingeniari* 'engineer', *enpresaburu* 'company director', *zinemagile* 'film maker', *informatikari* 'computer scientist', *igeltsero* 'bricklayer', *iturgin* 'plumber', *mekanikari* 'mechanic', *nekazari* 'farmer', *abeltzain* 'cattle farmer', *arrantzale* 'fisher', *sukaldari* 'cook', *albaitari* 'vet', *entrenatzaile* 'coach', *ikerlari* 'researcher', *zientzialari* 'scientist', *ikertzaile* 'investigator', *aholkulari* 'consultant', *aktore* 'actor', *youtuber* 'youtuber' |

**Table 2: List of occupations considered as female and male used in the study**

Having decided on the lists, we extracted the ST fragments (at paragraph level) containing the adjectives and occupations from Dabilena and translated them automatically using Elia. The resulting bilingual corpus was arranged in an Excel table and analysed manually. It should be noted that in the analysis phase, we only assessed whether the translation provided by the MT tool retained the gender of the ST. In other words, the quality of the machine translation was not assessed. Another important aspect of the methodology is that the ST units were presented together with their contextual information, i. e. accompanied by the preceding and following sentences. Thus, in some cases, it was possible to tell whether the occupation-related noun in the ST referred to a woman or a man (as it was explicit in either the previous or the following sentence), but gender bias was only assessed at sentence level, as this is how Elia currently operates.

The manual analysis phase could be summarised as follows:

1. Reading the ST.
   a. Checking the Basque ST to determine whether or not the occupation-related noun or adjective referred to a specific individual. If it did, we checked whether the gender was specified as male or female or could not be identified. If it did not, they were discarded.
2. Reading the target text (TT) provided by the MT tool.
   a. Checking whether the Spanish translation of the adjective or occupation referred to a man, a woman, or was omitted or not specified.
   b. Checking whether the gender marked in Spanish matched the (unmarked) gender in Basque.
   c. Checking whether the gender marked in Spanish matched the stereotype (as identified in the lists).

We set a maximum of 50 valid examples for each adjective and occupation in each type of text. In summary, when undertaking the initial step of reading the ST, examples that did not refer to individuals were discarded, while those that did were considered "valid". It should be noted that in some cases the number of examples in the corpus was considerably higher than the number finally analysed while in other cases the maximum of 50 valid examples was not reached.

Altogether, 11,631 valid units[8] were analysed in the study, of which 71.7% were occupations (8336 units) and 28.3% were adjectives (3214 units). The distribution regarding the type of text is the following:

- Literature: 4959 units
- News items: 3579 units
- Scientific texts: 3093 units

With regard to gender, in the case of occupations, units stereotyped as male are more abundant than those stereotyped as female (73.6% vs. 26.4%), whereas in the case of adjectives there are fewer male-stereotyped than female-stereotyped ones (48.4% vs. 51.6%).

Distributing the units by text type and gender (see Table 3), it is noteworthy that in scientific texts there are 163 adjectives stereotyped as masculine and only 66 stereotyped as feminine. In literature, 408 are masculine and 485 are feminine, and in news items 579 are masculine and 469 are feminine. In the case of occupations in general, the number of male examples is higher.

| | **Literature** | **News items** | **Scientific texts** |
|---|---|---|---|
| Male adjectives | 408 | 579 | 163 |
| Female adjectives | 485 | 469 | 66 |
| Male occupations | 1997 | 1207 | 1661 |
| Female occupations | 711 | 406 | 531 |

**Table 3: Corpus units by text type and gender**

## 4 Data analysis

This section presents the main findings of the study, highlighting key patterns and statistical outcomes. The results are organized to address the primary research questions and are interpreted in light of the study's objectives. Detailed analyses are provided in the following subsections.

### 4.1 Grammatical gender in the ST and its translation

As can be seen in Table 4, the difference between the two genders is more pronounced in the case of occupations. As far as the original texts are concerned, in the great majority of cases, the original units do not mark grammatical gender: this is the case for 72% adjectives considered as “male” and 60% of those considered as “female”, and 79% of occupations considered as “male” and 75% of those considered as “female”. These figures show that unmarked cases are more common in occupations and adjectives traditionally stereotyped as male.

[8] This figure does not include discarded units. Valid units account for only 45% of all units analysed.

| **Occupations** | **N** | **%** | | **N** | **%** |
|---|---|---|---|---|---|
| Male stereotyped | | | Female stereotyped | | |
| Masculine | 1004 | 16 | Masculine | 290 | 13 |
| Feminine | 168 | 3 | Feminine | 217 | 10 |
| Not specified | **4867** | **79** | Not specified | **1648** | **75** |
| Uncertain | 92 | 2 | Uncertain | 46 | 2 |

| **Adjectives** | **N** | **%** | | **N** | **%** |
|---|---|---|---|---|---|
| Male stereotyped | | | Female stereotyped | | |
| Masculine | 316 | 20 | Masculine | 279 | 16 |
| Feminine | 92 | 6 | Feminine | 368 | 22 |
| Not specified | **1151** | **72** | Not specified | **1011** | **60** |
| Uncertain | 37 | 2 | Uncertain | 41 | 2 |

**Table 4: Gender marks in original units in Basque**

Looking at the results obtained from Elia (see Table 5), we detected an overall trend: in cases where the original text does mark the gender, the machine translation tends to maintain it. For occupations, this is true of 94% of cases marked as male and 78% of cases marked as female; in the case of adjectives, it is true of 85% of cases marked as male and 80% of cases marked as female. As can be seen, the difference between genders is stronger in occupations than in adjectives. This may suggest a trend towards the use of the masculine gender when discussing occupations. In addition, in the case of both occupations and adjectives, maintenance of the assigned gender (Masc > Masc or Fem > Fem) is more frequent for words classified as male than for words classified as female. The frequency rate is very similar for female occupations (78%) and adjectives (80%).

| **Occupations** | **N** | **%** | | **N** | **%** |
|---|---|---|---|---|---|
| Masc > Masc | **941** | **94** | Fem > Fem | **170** | **78** |
| Masc > Fem | 12 | 1 | Fem > Masc | 30 | 14 |
| Masc > Not specified | 19 | 2 | Fem > Not specified | 13 | 6 |
| Masc > Omitted | 32 | 3 | Fem > Omitted | 4 | 2 |

| **Adjectives** | **N** | **%** | | **N** | **%** |
|---|---|---|---|---|---|
| Masc > Masc | **270** | **85** | Fem > Fem | **293** | **80** |
| Masc > Fem | 5 | 2 | Fem > Masc | 35 | 9 |
| Masc > Not specified | 13 | 1 | Fem > Not specified | 11 | 3 |
| Masc > Omitted | 28 | 9 | Fem > Omitted | 29 | 8 |

**Table 5: Translation of grammatical gender marked in the original as masculine (left) and feminine (right)**

Cases of male-to-female gender shift are marginal (1% in occupations and 2% in adjectives). It is also rare for the gender marked in the ST to disappear or become neutralised in the translation (Male or Fem > Not specified) or for the gender or fragment containing it not to be translated (Male or Fem > Omitted). The trend, if any, is to change from feminine to masculine, as can be seen in Table 5. The change from feminine to masculine is more evident in occupations than in adjectives.

In cases where the original text does not mark the gender, the result most frequently offered is male. As Table 6 shows, Elia's most common option is to translate both stereotypical female and male occupations and adjectives as male. Occupations are more often translated as male than are adjectives, and the trend is most significant in the case of occupations stereotyped as male and least significant in the case of adjectives considered as female. In the latter case ("female" adjectives), a considerable proportion of genderless units (28%) in the source text also have no specified gender in the translation. In the case of adjectives, quite a large number of genderless units are assigned no specific gender in translation. This may be one reason why the proportion of ungendered units translated as masculine is smaller in the case of adjectives than occupations. In addition, only a very small proportion of genderless original units have been translated as female. Amongst adjectives stereotyped as female, the proportion is only 10%, and in the case of occupations, although it is the second most frequent option (17%), it comes a significant distance behind the most common option.

| | **Male occupations** | | **Female occupations** | |
|---|---|---|---|---|
| | N | % | N | % |
| None > Masc | **4549** | **94** | **1256** | **76** |
| None > Fem | 71 | 1 | 282 | 17 |
| None > Not specified | 105 | 2 | 43 | 3 |
| None > Omitted | 140 | 3 | 67 | 4 |

| | **Male adjectives** | | **Female adjectives** | |
|---|---|---|---|---|
| | N | % | N | % |
| None > Masc | **791** | **69** | **531** | **53** |
| None > Fem | 66 | 5 | 100 | 10 |
| None > Not specified | 181 | 16 | 284 | 28 |
| None > Omitted | 112 | 10 | 95 | 9 |

**Table 6: Translation of grammatical gender in cases of genderless original units**

## 4.2 Gender inconsistencies at sentence level

Interestingly, when several occupations are mentioned in the same sentence, Elia does not always maintain gender consistency across them. Several cases have been identified mentioning *medikuak eta erizainak* 'doctors and nurses' in the ST that have been translated as *médicos y enfermeras* '(male) doctors and (female) nurses', as shown in Table 7.

| ST | MT |
|---|---|
| *Era berean, kontseilariak azaldu du egoera berriarekin Osasunbideak baliabide gehiago beharko dituela: besteak beste, **medikuak eta erizainak**.*<br>'The counsellor also explains that with the new situation, Osasunbidea will need more resources: among others, **doctors** and **nurses** [no gender].' | *Asimismo, la Consejera explica que con la nueva situación Osasunbidea necesitará más recursos, entre ellos **médicos y enfermeras**.*<br>'The counsellor also explains that with the new situation, Osasunbidea will need more resources: among others, **doctors** [male] and **nurses** [female]**.'** |

**Table 7: Example with more than one occupation in the same sentence**

As for adjectives, in cases where more than one is included there are many occasions in which a translated unit combines non-specified adjectives with gender-marked adjectives, as shown in Table 8. In the example given, *fieles* 'loyal (pl.)' and *obedientes* 'obedient (pl.)' could serve equally for males and females, but *sumisas* 'submissive (pl.)' is exclusively feminine.

| ST | MT |
|---|---|
| *Aurrerakoan, Toulouseko kondeak Frantziako Erregearen mendeko **leial, otzan eta esaneko** bihurtuko ziren, gizaldi batzuetarako.*<br>'From that moment on, the Counts of Toulouse became **loyal**, **docile** and **obedient** [no gender] to the King of France for a number of generations.' | *En el futuro, los Condes de Toulouse se convirtieron en **fieles, sumisas y obedientes** dependientes del Rey de Francia para varios siglos.*<br>'From that moment on, the Counts of Toulouse became **loyal** [no gender], **docile** [female] and **obedient** [no gender] to the King of France for a number of generations.' |

**Table 8: Example with more than one adjective in the same sentence**

### 4.3 Assigned stereotype and the MT tool output

We then explored whether the output from the MT tool coincided with the stereotype assigned in this study (see Table 9). We identified a significant difference between stereotypically male and female words (both adjectives and occupations). In a large percentage of occupations catalogued as male, Elia's translation matches the gender given in the source text (88.8%). A considerable proportion of adjectives catalogued as male were also translated with the same gender as the ST (68.8%), but the number of units translated with unspecified or female gender was higher than amongst the occupations. As for female words, non-matching with the ST gender (i. e. translating as masculine) was the most common option in both cases, although more frequent for occupations (61.0%) than for adjectives (47.0%). In both cases, only a limited number of units matched the original gender (25.8% and 23.3%, respectively). In the case of female adjectives, a particularly high proportion of translated units were of unspecified gender (29.7%).

| | Yes | No | Not specified |
|---|---|---|---|
| Male occupations | **88.8** | 3.1 | 8.1 |
| Female occupations | 25.8 | **61.0** | 13.2 |
| Male adjectives | **68.8** | 9.0 | 22.1 |
| Female adjectives | 23.3 | **47.0** | 29.7 |

**Table 9: Proportion in which the gender of the translation matches the gender specified in the original text**

These data show that gender is matched more often in the case of male stereotypes than female stereotypes. In addition, they show that there is a general tendency to translate occupations and adjectives as masculine.

## 4.4 Gender-neutral translations

For a qualitative assessment of the results, we should note that Elia sometimes tends to use inclusive language. The MT system gives split-gender results in some cases, although only in a limited number of units. In the example in Table 10, *hezitzaileak* 'educators' has been translated as *los educadores y educadoras* '(male) educators and (female) educators'.

| ST | MT |
|---|---|
| *Baina ematen dit zer pentsatua nahi duten guztia duten umeen irakasleek hainbeste eskatzeak eta baztertu ditugun umeen **hezitzaileek** behin eta berriz eskerrak emateak.*<br>'But it gives me a lot to think about the fact that the teachers of children who have everything ask so much and the **educators** [no gender] of children who have been rejected express gratitude again and again.' | *Pero me da lo que piensan que el profesorado de los niños y niñas que tienen todo lo que quieren les pida tanto y que **los educadores y educadoras** de los niños y niñas que hemos rechazado lo agradezcan una y otra vez.*<br>'But it gives me a lot to think about the fact that the teachers of children who have everything ask so much and the **educators** [male] and the **educators** [female] of children who have been rejected express gratitude again and again.' |

**Table 10: Example of gender splitting**

Another sign of inclusive language is the use of collective nouns. In the example in Table 11, *garbitzaileak* 'cleaners' has been translated as *personal de limpieza* 'cleaning staff'. Looking at the examples of the word *garbitzaile* in the literary texts of the corpus, we see that of the 61 examples of genderless units, 12 were translated without a specified gender, and in all such cases, inclusive language was used.

| ST | MT |
|---|---|
| ***Garbitzaileak*** *beheko solairuetan beste bi orduz egongo direla aurreikusi du.*<br>'The **cleaners** [no gender] are expected to stay on the ground floors for another two hours.' | *El* ***personal de limpieza*** *ha previsto que permanezcan otras dos horas en las plantas bajas.*<br>'The **cleaning staff** are expected to stay on the ground floors for another two hours.' |

**Table 11: Example of the use of collective nouns**

### 4.5 An additional challenge for MT systems: proper nouns

Identifying proper nouns should also aid the tool in deciding whether the individual in question is male or female. However, these names are not always sufficiently clear and the tool gives its results taking into account the stereotypes identified above. In the example in Table 12, mention of the female first name Rocío has not led Elia to identify the individual (correctly) as a female architect but instead (incorrectly) as an *arquitecto* 'male architect'.

| ST | MT |
|---|---|
| *Epaimahaia osatu dute: Felipe Juaristi idazleak, Juan Bautista Mendizabal Euskal Herriaren Adiskideen Elkarteko lehendakariak,* ***Rocio Peña arkitektoak****, […].*<br>'The jury was composed of the writer Felipe Juaristi, the president of the Association of Friends of the Basque Country, Juan Bautista Mendizabal, **the architect** [no gender] **Rocio Peña**, [...].' | *El jurado ha estado compuesto por el escritor Felipe Juaristi, el presidente de la Real Sociedad Bascongada de Amigos del País, Juan Bautista Mendizabal,* ***el arquitecto Rocío Peña****, [...].*<br>'The jury was composed of the writer Felipe Juaristi, the president of the Association of Friends of the Basque Country, Juan Bautista Mendizabal, **the architect** [male] **Rocio Peña**, [...].' |

**Table 12: Examples of the translation of proper names**

## 5 Conclusions

In the Basque language, gender is not marked grammatically. However, it may be specified through the use of other types of information within the sentence. In our research project and in the corpora used for this purpose, this phenomenon occurs in a limited number of instances (less than a third of the examples). In most such cases, the MT tool, Elia, maintained the gender specified in the original unit. This gender matching is seen both for adjectives (Male > Male, 85% and Fem > Fem, 80%) and for occupations (Male > Male, 94% and Fem > Fem, 78%).

In the majority of cases, however, the original Basque text did not indicate the gender at sentence level. It is worth noting that on numerous occasions, the gender of the original unit could be deduced from the broader context beyond sentence level. However, this was not considered, as MT tools operate at sentence level and do not consider contextual information.

Some similar contemporary studies (cf. Monzó-Nebot/Tasa-Fuster 2024) have found that MT tools tend to favour the masculine. This tendency is also evident in the present case, as observed in Elia. However, this predilection is more pronounced when it comes to occupations than adjectives. Amongst male-stereotyped occupations, the tool opted for the masculine (No > Masculine) in 94% of cases, a significant 25 points higher than its equivalent use of the masculine for male-stereotyped adjectives (69%). In the case of occupations stereotyped as female, Elia opted for the masculine in 76% of cases, 23 points more than in the case of adjectives (53%). This suggests that gender bias may be more pronounced in the context of occupations, potentially reflecting actual societal biases.

Despite the heterogeneity of the text types included in the study (journalistic, scientific and literary), no significant disparities were observed between the text types.

In addressing the research questions posed in this study, it has been observed that when translating from a language that only marks gender lexically to a language that marks it morphologically, Elia almost always uses the masculine in the translation. However, it is important to note that some instances have been observed in which the MT tool has produced gender-neutral translations or has made use of a gender-inclusive slash thereby demonstrating its capacity to circumvent gender bias. This suggests that while it has an evident gender bias, it can also employ strategies to mitigate it.

In addition to the initial objectives, the research has also raised new reflections. To mitigate gender bias, MT tools should be trained to identify more proper nouns and offer neutral or slash-type alternatives. However, it is important to note that such options may not be suitable for all textual types, particularly literary ones, and help to perpetuate the existing binary structure of our society (cf. Rico Pérez/Martínez Pleguezuelos 2024: 261). This suggests that a nuanced approach is needed that takes into consideration the specific nature of each text type. It is evident that collaboration from translators is imperative in developing novel MT solutions, and their involvement in post-editing MT translations is equally crucial.

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