Conscious Bias in Thailand Job Posting

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Received : 21 September 2024 / Revised : 25 October 2024 / Accepted: 4 November 2024

Abstract This research paper investigates the presence of conscious bias in LinkedIn job postings within Thailand, focusing on gendered language and its impact on recruitment practices. Conscious bias, manifested through explicit preferences in job descriptions, can perpetuate inequality in the labor market. By analyzing job postings across ten in-demand roles in the tech and data-driven sectors, this study identifies patterns of gendered language and explores their implications for gender diversity in recruitment. By tokenization techniques in Natural Language Processing (NLP) , the research reveals that masculine-coded language is more prevalent in technical roles, potentially discouraging female applicants and contributing to the underrepresentation of women in leadership and senior positions. Additionally, the paper highlights the role of educational requirements as a barrier to inclusivity, particularly in fields that favor candidates with advanced degrees. The findings underscore the need for more inclusive job postings and greater enforcement of anti-discrimination policies to promote equality in the Thai labor market.

Keywords: Conscious bias, Gendered language, Gender diversity, Anti-discrimination policies

1. Introduction

The digitalization of recruitment practices has transformed how job opportunities are posted and accessed, with LinkedIn emerging as a significant platform for both employers and job seekers. However, despite the advantages of this digital shift, there are growing concerns about the existence of conscious bias in job postings on LinkedIn, particularly in the context of Thailand. Conscious bias refers to deliberate or explicit prejudice that affects decision-making processes, often manifesting in discriminatory language or practices [1]. Previous studies highlight how recruitment platforms can unintentionally propagate biases, particularly in terms of gender, age, and race [2]. In Thailand, these biases often reflect societal norms and cultural expectations, which can influence how employers frame job advertisements. For instance, research by Thamsuk et al. [3] underscores that job postings in Thailand may perpetuate gender-based expectations, such as preferring male candidates for technical roles, which reflects broader socio-cultural dynamics.

Moreover, conscious bias extends beyond gender, impacting areas such as educational background, age, and appearance, all of which are commonly mentioned criteria in Thai job postings [4]. This paper aims to explore how conscious bias manifests in LinkedIn job postings in Thailand and the potential implications for equality and inclusiveness in the labor market. By drawing on relevant academic literature and analyzing real-world examples, this study will shed light on the underlying factors contributing to conscious bias and propose solutions for creating more equitable recruitment practices.

While LinkedIn offers a platform where job seekers and employers can connect globally, it has also been observed that the content and structure of job advertisements may reflect conscious or implicit biases, affecting the inclusiveness of the recruitment process [5]. Conscious bias in job postings can often be subtle but impactful, especially when employers include specific requirements that may disadvantage certain groups. For example, phrases such as "young and energetic" or "male preferred" indicate clear preferences, which can discourage potential applicants from diverse backgrounds [6]. In Thailand, societal expectations, such as favoring candidates with a certain appearance or those who have graduated from well-known universities, further exacerbate these biases [3]. By examining job advertisements on LinkedIn through the lens of conscious bias, this study aims to identify recurring patterns and propose actionable steps to mitigate bias in recruitment, thus fostering a more inclusive hiring landscape.

1.1 Conscious and Unconscious Bias in Job Postings

The literature on bias in job descriptions reveals several types of biases that influence recruitment outcomes, often perpetuating inequality. Gender bias is one of the most studied forms, with research showing that language in job descriptions often favors male candidates for leadership and technical roles. For instance [7], highlight how gender stereotypes influence employers' perceptions, particularly in male-dominated industries like technology and engineering. This bias, reinforced by terms like "assertive" or "competitive," can dissuade women from applying, especially for senior roles due to stereotypes about their leadership abilities [8].

Racial and ethnic bias is similarly pervasive. Bertrand and Mullainathan's [9] landmark study demonstrated that candidates with "ethnic-sounding" names were significantly less likely to receive callbacks for interviews compared to those with traditionally "white-sounding" names, even when qualifications were identical. Such biases can be present in job descriptions through culturally specific language or assumptions that may alienate minority candidates [10].

Age bias is another form of discrimination embedded in recruitment practices, especially when job descriptions use phrases like "young, dynamic team." Older job seekers, particularly those over 50, are often viewed as less adaptable and technologically proficient compared to younger candidates [11]. This is especially prevalent in industries such as IT and marketing, where youth is often equated with innovation and adaptability [12].

In addition, disability bias is frequently found in job descriptions that emphasize physical or sensory requirements, even when such abilities may not be essential for the role. These unnecessary requirements can discourage individuals with disabilities from applying, limiting their opportunities [13]. Finally, educational and experience bias can also be present, with job descriptions sometimes requiring degrees from prestigious institutions or an excessive number of years of experience, which disproportionately excludes candidates from diverse educational backgrounds or younger, less experienced applicants.

Addressing these biases requires a deliberate effort to revise job descriptions, focusing on neutral, inclusive language that emphasizes essential qualifications rather than perpetuating stereotypes or unnecessary requirements. Such changes are critical for fostering more equitable hiring practices and promoting diversity within organizations.

1.2 Job Posting Quantitative Analysis Methods

Building on the foundational studies of gendered word usage in job descriptions, recent research has emphasized the role of language in reinforcing gender stereotypes. For instance, Kay, Gaucher, and Friesen [14] discovered that certain masculine-coded words, particularly those representing agency and dominance, are more likely to deter female applicants. This concept aligns with Shiliang Tang's [15] work, which demonstrated that gender stereotypes could be quantified through algorithms that analyze self-reported characteristics. Meanwhile, Matfield's [16] development of the Gender Decoder tool introduced a practical application that measures the frequency of gender-coded words in job descriptions, albeit without fully capturing the contextual meaning of those words.

More recent advancements in this field, such as Dikshit et al.'s [17] use of Natural Language Processing (NLP), provide a more comprehensive approach by categorizing job descriptions into agentic, communal, or balanced types. This method represents a significant improvement, as it enables a more nuanced understanding of how language in job descriptions either attracts or deters applicants of different genders. However, as gender bias remains an ongoing issue, particularly in specific cultural contexts like Thailand, where patriarchal values often restrict women from attaining leadership positions, these tools must be continually refined and validated for broader, more inclusive applications.

1.3 Discrimination in Hiring Practices in the Thai Labor Market

Discrimination in hiring practices is a significant issue in many countries, including Thailand. Research has shown that biases based on gender, age, and ethnicity influence employment opportunities and outcomes in the Thai labor market. Rigg and Ritchie [18] highlighted that women in Thailand face challenges in accessing leadership roles and jobs in male-dominated fields, such as engineering and technology. This is often due to stereotypes about women's commitment to work and assumptions about their family responsibilities. Similarly, Tangkitvanich and Sasiwuttiwat [19] noted a persistent wage gap between men and women, partially attributed to discriminatory hiring practices that prevent women from securing high-paying positions. Gender norms remain deeply embedded in Thai society, as UN Women [20] reported, further limiting women's opportunities in the workforce.

Age discrimination is another prevalent issue in Thailand. Praemai and Intarakumnerd [21] found that older workers, particularly those over 40, are often overlooked in favor of younger candidates, even when they have relevant experience. This bias is rooted in perceptions that older workers are less adaptable to new technologies and workplace environments. Despite policies that encourage the employment of older individuals, as noted by Chantanusornsiri [22], these initiatives are not widely enforced, leaving many older job seekers at a disadvantage, particularly in fields like marketing and technology.

Ethnic discrimination also plays a significant role in Thailand's hiring practices, especially against migrant workers from neighboring countries like Myanmar, Cambodia, and Laos. The International Labour Organization (ILO) [23] documented instances of ethnic bias, where migrant workers are often relegated to low-wage, low-skill jobs regardless of their qualifications. Suwanarak [24] emphasized that ethnic minorities and migrant workers face barriers such as language difficulties and social exclusion, which prevent them from accessing better job opportunities. Legal restrictions further limit the types of jobs that non-Thai workers can apply for, exacerbating their marginalization.

While Thailand has introduced legislation such as the Labour Protection Act (1998) and the Gender Equality Act (2015) to address discrimination, the enforcement of these laws remains weak. Chun [25] argues that while these laws are a step in the right direction, more stringent enforcement is necessary to combat discrimination effectively. The National Human Rights Commission of Thailand [26] has called for stronger enforcement and public awareness campaigns to challenge societal attitudes that perpetuate bias in the workplace.

1.4 Hiring Practices in the Tech Sector in Thailand and Beyond

Globally, discrimination in hiring practices within the tech sector remains a critical issue, particularly concerning gender, race, and age. Women, in particular, face substantial barriers, with 57% reporting gender-based discrimination, compared to only 10% of men. Racial discrimination is also prevalent, especially for Black and Hispanic employees, who are more likely to experience bias and are often underrepresented in higher-paying roles. Efforts to promote diversity, equity, and inclusion (DEI) have increased, but the industry still struggles to close gaps in gender and racial equality (World Economic Forum, 2023).

In Thailand, the tech sector reflects global trends of gender and age discrimination, where women are frequently perceived as lacking the technical expertise required for leadership roles and advanced positions. This perception contributes to their underrepresentation in key decision-making roles and mirrors broader gender biases observed across multiple industries. Despite some available evidence, much of the research in this area remains qualitative, and there is a gap in rigorous academic studies that explore these biases in depth. Given the significant role job postings and recruitment practices play in shaping career opportunities and considering the rapid growth of Thailand's tech sector, this paper seeks to closely examine the prevalence and impact of discrimination in hiring practices. By doing so, it highlights the need for more systematic studies and stronger policy enforcement to promote a more equitable labor market.

2. Analysis and Methodology

This study employs a rigorous data collection process to investigate potential biases in job postings on LinkedIn, focusing on the ten most popular job positions in Thailand. The goal of this research is to uncover any patterns of bias that may exist in hiring practices based on factors such as job description language, seniority levels, and other relevant factors. The data was collected through automated web scraping using the tool Octoparse, which allowed for precise and efficient extraction of job-related information.

2.1 Scope of the Study

The research is confined to job postings within Thailand, ensuring the geographic relevance and context specificity of the data. Based on a LinkedIn article highlighting the most in-demand roles, the following ten job positions were selected for analysis: Software Engineer, DevOps Engineer, Solution Architect, Data Analytics, Data Engineer, Data Scientist, Business Analyst, Product Design (UX/UI), IT Manager, Cyber Security [28].

These roles represent a diverse array of industries, predominantly within the technology and IT sectors, making them ideal candidates for a detailed analysis of job bias in the hiring landscape.

2.2 Data Collection

The data scraping was performed using Octoparse, a powerful web scraping tool that allows for the automated extraction of data from websites. Octoparse was configured to target LinkedIn job postings, specifically focusing on jobs listed under the aforementioned ten popular positions. The tool extracted the following key fields from each job posting: Keyword: The job-related keyword used to classify and categorize positions. Location: The specific geographic location of the job, ensuring the job is based in Thailand. Job Title: The title of the position as listed by the company. Company: The name of the company offering the job. Job Location: Further details on where the job is located, such as the city or region within Thailand. Job Description: The full job description provided by the employer, which includes required qualifications, responsibilities, and any other details. Industry: The sector or industry to which the job belongs, such as IT, healthcare, or finance. Employment Type: Whether the job is full-time, part-time, contractual, or internship-based. Valid Through: The date the job posting expires or is no longer valid. Seniority Level: The required level of experience for the job, such as entry-level, mid-level, or senior-level positions. Job Function: The main role or department within which the job falls, such as engineering, management, or design.

The following steps were applied to ensure that only relevant and high-quality data were collected: Geographic Focus: Only job postings based in Thailand were included, eliminating irrelevant listings outside the scope of this study. Keyword Selection: To ensure relevant positions were targeted, keywords were carefully chosen to reflect a variety of popular roles across different sectors, informed by market research and current job trends. Time Frame: Job postings were limited to a specific time frame, ensuring that the analysis focused on current job market trends in Thailand. Duplicate and Outlier Handling: Any job posting that appeared multiple times due to different application links was consolidated to avoid redundancy.

This comprehensive dataset was then structured to allow for further analysis. The scraping process was refined to ensure that only relevant job postings within Thailand were collected, eliminating any extraneous data from outside the geographic scope of the study.

2.3 Gender Bias Detection Using NLP

The detection of gender bias in job postings was facilitated by applying Natural Language Processing (NLP) techniques to analyze job descriptions. A predefined list of masculine-coded and feminine-coded words, derived from established research, was used to classify the language within each job posting. Text Preprocessing: Job descriptions were cleaned and tokenized to standardize the text, removing irrelevant characters and breaking the descriptions into individual words. Keyword Matching: Using NLP, each job description was analyzed to detect the frequency of masculine-coded words (e.g., "dominant", "competitive") and feminine-coded words (e.g., "supportive", "collaborative"). Bias Categorization: Descriptions were categorized as masculine-biased, feminine-biased, or neutral based on the dominance of gender-coded words. This categorization enabled the identification of unconscious gender bias trends across various job sectors and roles.

This NLP-based approach provided a systematic and data-driven method for detecting and analyzing gender bias in the recruitment process.

2.4 Data Cleaning and Preprocessing

Preprocessing the data is a critical step in ensuring the accuracy and reliability of the analysis. This process involves several stages, including data cleaning, transformation, and the application of bias-detection methodologies. The following sections outline the procedures undertaken to prepare the dataset for analysis.

2.4.1 Data Cleaning

The initial stage of preprocessing involved addressing inconsistencies, missing data, and duplicates within the dataset. Ensuring the dataset is clean and consistent is essential for producing valid results, particularly when analyzing text data for gender bias.

Missing Data Treatment: An examination of the dataset revealed some missing values across various fields. Since the focus of the analysis is on the textual content within the job_description field, any rows where this variable was missing were removed, as the absence of this field would prevent the detection of potential biases. Other missing values, such as in the applicant_count or job_location fields, were addressed using median imputation or left unfilled where appropriate, as they were not critical to the primary analysis.

Duplicate Removal: Duplicate entries in the dataset were identified based on several key fields, including job_title, company, and job_description. Importantly, the job_link field was excluded from this process, as different links may direct to the same job posting. This ensured that identical job postings were not counted multiple times, thereby avoiding redundancy in the analysis.

2.4.2 Gender Bias Detection

The key objective of this research is to detect unconscious gender bias in job descriptions. Drawing on prior studies of gendered language in job advertisements [14], a predefined list of masculine-coded and feminine-coded words was utilized. Masculine-coded words, such as "dominant", "competitive", and "analytical", are often associated with leadership and assertiveness, traits culturally aligned with male stereotypes. In contrast, feminine-coded words, such as "supportive", "understanding", and "collaborative", are linked to nurturing and communal roles, which align with female stereotypes. The following steps were taken to apply gender bias labeling:

Keyword Matching: Each job description was analyzed for the presence of words from both the masculine-coded and feminine-coded lists. The frequency of these words within each description was recorded.

Bias Categorization: Based on the balance of masculine-coded and feminine-coded words, each job description was classified as either: Masculine-biased if masculine-coded words predominated, Feminine-biased if feminine-coded words were more frequent, or Neutral if neither type of word showed significant dominance. This categorization enables a systematic analysis of gender bias trends across different industries, seniority levels, and job functions.

2.4.3 Seniority Level and Job Function

The seniority_level field was already well-structured into distinct categories, including entry-level, mid-level, and senior-level positions. Given the structured nature of this field, no further preprocessing was required. The categorization provided a direct means of analyzing how unconscious bias may manifest differently across hierarchical levels in the workforce. For instance, previous studies suggest that higher-level positions may feature more masculine-coded language, which could contribute to the underrepresentation of women in leadership roles [29].

2.4.4 Industry Breakdown

A statistical breakdown of the data revealed notable differences in the use of masculine and feminine-coded language across industries. Industries such as IT Services and Consulting had significantly higher counts of masculine-coded words. For example, the IT sector recorded 1,112 occurrences of masculine-coded language, compared to 826 feminine-coded terms across all job postings. This disparity suggests that the descriptions in this industry tend to emphasize traits traditionally associated with men, such as competitiveness, leadership, and analytical skills. IT Services: This industry had a masculine-coded language count of 1,112 words, compared to 826 feminine-coded words. Consulting: Consulting roles featured a similar trend, with 940 masculine-coded terms and only 710 feminine-coded words.Retail: In contrast, the retail industry exhibited more balanced language, with 525 masculine-coded words and 498 feminine-coded terms, reflecting a more neutral approach to gendered language.

This imbalance may reflect an unconscious bias that favors male applicants for technical and leadership roles, while the more balanced language in retail could indicate a conscious effort to appeal to a broader and more diverse talent pool.

2.4.5 Job Position Breakdown

The analysis also revealed significant gendered language patterns when breaking down the data by job titles or keywords. Certain job roles, particularly in technical fields, displayed a clear skew towards masculine-coded language. For example:

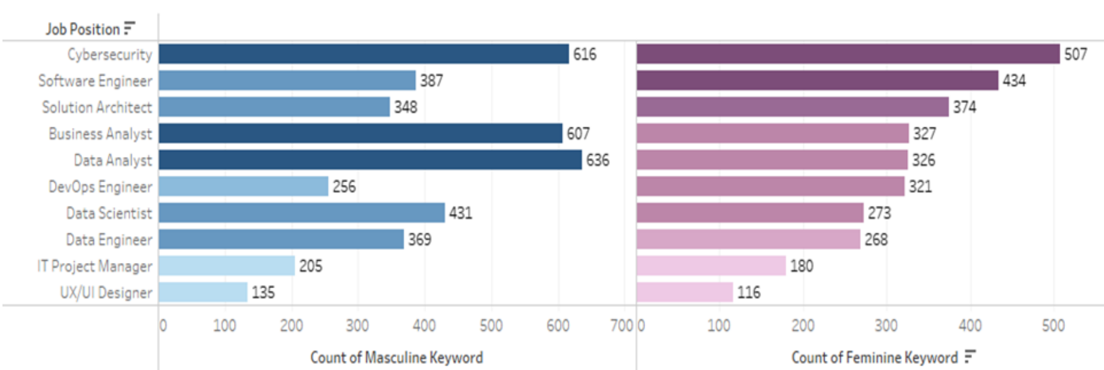

Fig.1 Masculine and Feminine Keyword Usage Across Job Positions

Data Analyst roles featured 636 masculine-coded terms and 326 feminine-coded terms across 102 job postings. Cybersecurity roles showed a similar trend, with 616 masculine-coded words and 507 feminine-coded terms across 128 job postings. Business Analyst roles had 607 masculine-coded terms and 327 feminine-coded terms across 102 job postings.

These findings indicate a preference for masculine-coded language in analytical and data-driven roles. This could signal an unconscious bias where qualities like problem-solving, analysis, and competitiveness are emphasized, traits that are traditionally associated with men. In contrast, positions such as Software Engineer showed a more balanced language use, with 387 masculine-coded words and 433 feminine-coded words, suggesting that there are efforts within the technology sector to reduce gender bias in job descriptions for certain roles.

For statistical analysis, we are interested in the difference in the usage of masculine and feminine words across job roles and vice versa.

ANOVA

Source of Var	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Rows	318024	9	35336	4.1037	0.0236	3.1789
Columns	37324.8	1	37324.8	4.3347	0.0670	5.1174
Error	77496.2	9	8610.69			
Total	432845	19				

Fig.2 ANOVA Result between Masculine and Feminine Keyword

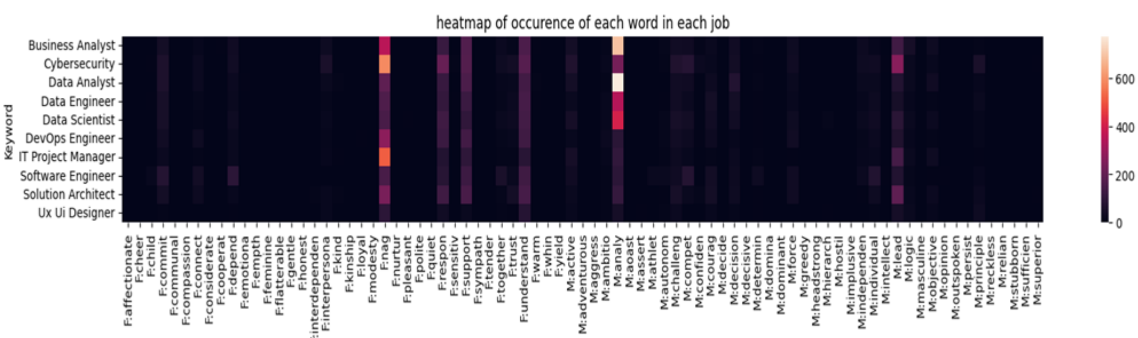

Fig.3 Dependency between Word Choice and Job

ANOVA table indicates that the difference in the usage of masculine and feminine words across different job roles is statistically significant. In other words, The job role has a significant impact on the proportion of masculine and feminine words used. In other words, the choice of job role affects how much masculine or feminine language is used. However, there is no strong evidence to conclude that the overall usage of masculine and feminine words differs significantly, but it may be worth investigating further, as it is close to the significance threshold.

2.4.6 Overall Gender Bias Trends

In total, masculine-coded words were more prevalent than feminine-coded words across most industries and job roles. Across the dataset, there were 4,560 masculine-coded words compared to 3,320 feminine-coded words, indicating a potential unconscious bias favoring masculine traits in job descriptions. The data-driven and technical industries showed the greatest imbalance, which may suggest that these fields have a tendency to emphasize qualities traditionally associated with male candidates. On the other hand, sectors like retail demonstrated more balanced language, which could reflect conscious efforts to appeal to a wider audience.

2.4.7 Dependency Test between Word Choice and Job

Among masculine words, Chi-squared test, we get χ^2=2664.573 with df = 252. Then P-value = 0. That is, no dependency between word masculine word choice and the type of job. Similarly, for feminine words, χ^2=1330.1 with df = 207. Then P-value = 0. That is, no dependency between word feminine word choice and types of job

2.4.8 Graduate Degree

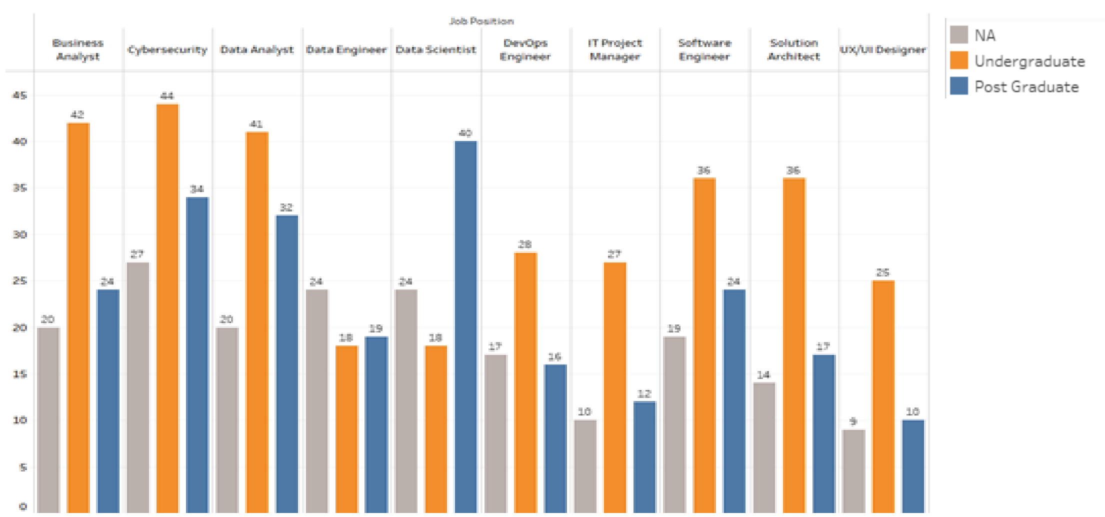

Fig.4 Distribution of Undergraduate and Postgraduate Degree Requirements Across Job Position

We count (1) not mentioning a graduate degree, (2) requiring an undergrad degree, and (3) including a postgrad degree; the data science field tends to prefer a higher degree.

Job Position	NA	Bachelor	Master	Phd
Business Analyst	20	42	23	1
Cybersecurity	27	44	24	10
Data Analyst	20	41	31	1
Data Engineer	24	18	18	1
Data Scientist	24	18	32	8
DevOps Engineer	17	28	14	2
IT Project Manager	10	27	12	0
Software Engineer	19	36	15	9
Solution Architect	14	36	17	0
UX/UI Designer	9	25	9	1

Fig.5 Degree-Level Requirements (Bachelor, Master, PhD) Across Job Descriptions

If drilling down to master degree and PhD, PhD holders are rare across most roles, except for Cybersecurity and Software Engineering, where niche expertise may be required. Both the job roles (Rows) and education levels (Columns) show significant effects, implying that the educational requirements vary across job roles and that different education levels are distinctly distributed across the job roles. It also indicates significant differences in both factors.

3. Result and Discussion

3.1 Gender Bias in Job Postings

The analysis of job descriptions revealed a noticeable pattern of gender bias, with masculine-coded words being more prevalent than feminine-coded words across most industries and job roles. Out of the total dataset, 4,560 masculine-coded words were identified compared to 3,320 feminine-coded words. This imbalance highlights a potential unconscious bias towards masculine traits in job advertisements, particularly within data-driven and technical fields.

Specifically, roles such as Data Analyst, Cybersecurity, and Business Analyst featured significantly more masculine-coded terms compared to feminine-coded ones, reflecting an emphasis on qualities traditionally associated with men, such as competitiveness and assertiveness. For instance, Data Analyst job descriptions contained 636 masculine-coded words compared to 326 feminine-coded words across 102 postings. Similarly, Cybersecurity roles showed 616 masculine-coded words and 507 feminine-coded words across 128 postings. This trend suggests that employers in these industries may be unconsciously favoring male candidates by highlighting traits typically associated with men.

On the other hand, certain positions, such as Software Engineer, displayed a more balanced language use, with 387 masculine-coded words and 433 feminine-coded words, indicating some progress toward reducing gender bias in technical fields. Meanwhile, industries like retail demonstrated relatively balanced language, with 525 masculine-coded terms and 498 feminine-coded terms, reflecting a conscious effort to appeal to a broader and more diverse talent pool.

3.2 Industry Breakdown

The study found that bias patterns varied significantly across industries. The IT Services and Consulting sectors exhibited the highest masculine-coded language counts, with 1,112 and 940 occurrences, respectively. These industries tend to emphasize traits such as leadership, competitiveness, and analytical skills, which may unconsciously favor male applicants. In contrast, the retail sector displayed a more neutral approach, with a near-equal use of masculine and feminine-coded terms, suggesting that employers in retail are making a conscious effort to promote inclusivity.

3.3 Seniority Levels and Job Functions

The use of masculine-coded language was more pronounced in job descriptions for senior-level roles, particularly in technical and leadership positions. This aligns with previous research suggesting that masculine traits are often emphasized in leadership roles, potentially deterring women from applying for these positions. In contrast, entry-level roles tended to use more neutral language, which may indicate that employers are more focused on inclusivity at the early stages of the hiring process but revert to traditional stereotypes at higher levels of seniority.

3.4 Educational Bias

The analysis of educational requirements revealed that certain fields, particularly Data Science and Cybersecurity, tended to favor candidates with advanced degrees. This preference for higher education may disadvantage candidates from diverse backgrounds who may not have had access to prestigious universities or postgraduate programs. The requirement for advanced degrees was more prevalent in technical roles, while industries such as retail and consulting were more likely to list undergraduate degrees or no degree requirements at all.

3.5 Statistical Analysis of Bias

The chi-squared tests conducted to assess the dependency between word choice and job type found no significant dependency between the use of masculine or feminine-coded words and the type of job. This suggests that the language used in job descriptions is not necessarily tailored to specific roles but may reflect broader, industry-wide trends in unconscious bias. Additionally, the preference for graduate degrees in fields like Data Science further emphasizes the barriers that certain groups, such as women or candidates from underrepresented backgrounds, may face when applying for these positions.

4. Conclusion

The findings of this study underscore the prevalence of conscious and unconscious bias in LinkedIn job postings within Thailand's tech sector. Masculine-coded language dominates job descriptions, particularly in technical and data-driven fields, where leadership, competitiveness, and analytical skills are often emphasized. Which is in accordance with the assumptions and objectives revealing that most biases tend to favor men, particularly in the technology and data-driven industries. Additionally, we discovered that job postings in Thailand still contain biases in various aspects, such as gender, age etc., which may prevent diverse groups of candidates from accessing job opportunities. This bias could contribute to the underrepresentation of women and other minority groups in these industries by discouraging them from applying to roles that emphasize qualities traditionally associated with men.

Although some industries, such as retail, have made strides toward more inclusive job advertisements, the tech sector still has significant work to do in promoting gender equality in recruitment practices. The bias observed in senior-level roles suggests that traditional gender stereotypes persist, particularly in leadership positions, further limiting the opportunities for women in male-dominated fields.

Educational requirements also present a barrier to diversity, with technical roles often requiring advanced degrees, which can disproportionately exclude candidates from less privileged backgrounds. These findings highlight the need for a concerted effort to revise job descriptions to remove unnecessary and biased requirements, focusing instead on inclusive language that promotes diversity and equality in hiring.

To address these biases, organizations must prioritize neutral and inclusive job descriptions, provide bias-awareness training for recruiters, and implement tools that detect and mitigate unconscious bias. By fostering more equitable hiring practices, companies in Thailand’s tech sector can create a more diverse and inclusive workforce, benefiting from a wider range of talent and perspectives.

For recommendations to reduce bias 1.Adopt Neutral and Inclusive Language like Review job descriptions to ensure the use of gender-neutral terms. Replace masculine-coded language (e.g., "competitive," "assertive") with more inclusive alternatives like "collaborative" or "strong communicator."or Use language-analysis tools to detect and remove biased language before posting. 2.Prioritize Skills Over Traits like Focus job descriptions on the essential skills and qualifications needed for the role rather than personality traits traditionally associated with one gender. And Avoid vague terms like "leadership" that may unconsciously favor men, and instead describe specific competencies relevant to the job. 3.Reconsider Educational Requirements like Reevaluate the need for advanced degrees, especially in technical roles, to avoid disproportionately excluding candidates from diverse or underprivileged backgrounds or Prioritize experience, practical skills, and potential over formal education credentials. 4.Leverage Bias Detection Tools like Utilize software tools that analyze job postings for biased language and provide suggestions for more neutral phrasing. This can help ensure that job descriptions are accessible and appealing to a broader and more diverse talent pool. 6.Implement regular training for recruiters and HR staff to recognize and mitigate conscious and unconscious biases in recruitment practices, from writing job descriptions to screening candidates.

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