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# HOW IMAGE GENERATION SYSTEMS DEMONSTRATE STEREOTYPES: EVIDENCE FROM THE CHINESE AI SYSTEM WENXINYIGE

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## ABSTRACT

***As Artificial Intelligence (AI) applications expand across diverse domains, questions of bias, discrimination, and social justice have become central to the field of AI ethics. While international scholarship has examined how generative systems such as DALL·E and Midjourney reproduce cultural and gendered stereotypes, far less attention has been paid to non-Western contexts. This study addresses this gap by analysing Wenxinyige, a representative Chinese image generation platform, through the Walkthrough Methodology. The research investigates how Wenxinyige encodes gendered assumptions in its outputs, focusing on representations of occupation, appearance, behaviour, and personality. Findings demonstrate that Wenxinyige consistently reinforces patriarchal cultural logics, demonstrating occupational stereotypes and age discrimination. Women are portrayed as youthful, attractive, and submissive, while men are associated with authority, occupational prestige, and active roles. These patterns extend beyond surface-level representation, functioning as a mechanism of algorithmic disciplining that shapes users' perceptions of gender norms and age hierarchies. In doing so, the system exacerbates digital inequalities and contributes to the marginalisation of particular social groups. By situating Wenxinyige within global debates on algorithmic justice, this study expands the largely Western-centred scholarship on AI bias to include the Chinese context. It underscores that generative AI systems are not neutral creative tools but socio-technical artefacts that reflect and reproduce existing inequalities. The findings underscore the pressing need for more inclusive data practices, increased transparency in model design, and robust governance frameworks that safeguard human rights and foster digital justice.***

**KEYWORDS:** Artificial Intelligence; AI Ethics; Algorithmic Justice; Gender Bias; Digital Inequalities.

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## 1. INTRODUCTION

We are entering an era in which Artificial Intelligence (AI) is deeply embedded in and substantially altering various aspects of modern life (Ahn et al., 2022). As AI use continues to increase, so does the discussion of its strengths and limitations. It is now widely recognised in academia that AI is a collection of contradictions, with both advantages and disadvantages. Some scholars describe their strengths as permanency, reliability, and cost-effectiveness (Chowdhury & Sadek, 2012; Kazim & Koshiyama, 2021; Waisi, 2020), while others simultaneously mention bias, disinformation, and encouraging opacity as limitations (Banh & Strobel, 2023; Manyika, 2022). The study of these shortcomings gave birth to the research field of AI ethics (Kazim & Koshiyama, 2021). Recognising that ethical issues are relevant to any platform that utilises AI, Stahl (2021) identifies 39 problems associated with the use of these technologies. This thesis focuses on one of these issues: bias and discrimination. This paper focuses on one of the representative image generation systems: Wenxinyige, examining how its outputs reflect and reproduce gendered bias. Using the walkthrough methodology, this study analyses how the system encodes stereotypes and embeds unequal social values into visual outputs. Image generation systems, such as Wenxinyige, not only create novel cultural artifacts but also shape social understandings of identity, beauty, and gender roles. As such, their influence extends beyond technological novelty, carrying significant implications for questions of algorithmic justice, discrimination, and digital inequalities. This article situates Wenxinyige within broader debates on AI ethics and human rights, asking: How does a Chinese image generation system reproduce gender stereotypes, and what does this reveal about bias and discrimination in AI?

By exploring the intersection of technology, gender, and cultural representation, the study demonstrates how generative AI can amplify existing inequalities, particularly by reinforcing patriarchal norms and marginalising female identities. In doing so, it underscores the urgent need for more inclusive and equitable approaches to AI development, highlighting the broader societal responsibility to protect marginalised communities and safeguard digital justice.

## 2. LITERATURE REVIEW

### *2.1. Artificial Intelligence and Current Study Summary*

Currently, no widely accepted definition of AI exists (Wang, 2019). There is a long history and a continuing practice of defining AI in terms of equivalence or advancement to human cognitive function. AI is considered an umbrella term, encompassing various computational algorithms that utilize computers and data to simulate problem-solving and decision-making abilities traditionally associated with human cognition. Sometimes, AI can be a program with better abilities than humans (Banh & Strobel, 2023; Dobrev, 2012; Zhang et al., 2021; X. Zhou et al., 2012; Zhu et al., 2024). With the increasing application of AI, research into these technologies has grown. Many scholars focus on the merits of specific AI technologies applied in particular scenarios (Chowdhury & Sadek, 2012; Kazim & Koshiyama, 2021; Waisi, 2020). However, unlike traditional approaches that solely examine the specific advantages and disadvantages of particular artificial intelligence implementations, this paper focuses on the social consequences of these technologies, including their connection to human behaviours, and thus explores the social changes and political implications they can generate. This sociotechnical focus is why this paper prioritises AI ethics, a human-centred field concerned with how AI can better provide value to humans. Based on the ethical principle of human equality, fairness is a central theme in AI ethics, aiming to ensure the participation of all groups and prevent marginalization. Kazim & Koshiyama (2021) recommend that studies seeking to promote equity should consider three key themes: prejudice, accessibility, and participation. Within the realm of ethics and bias, the study of gender bias is a vital branch, particularly given that current feminist movements and activities are increasingly conducted online through digital platforms (Mohajan, 2022).

By adopting this approach, I join a growing body of scholarship that explores AI and gender bias, intersecting the humanities and computer science disciplines, and combines feminist, sociological, and anthropological frameworks. For example, Borau (2025) employs an existential feminist perspective and techno-feminism to analyse how the design of female-oriented AI perpetuates normative femininity, thereby reinforcing stereotypes of women and creating a distorted image of women in the minds of men, while also misrepresenting women's identities. In the field of linguistics, Kopeinik et al. (2023) used prototype theory to analyse how gender-biased search engines can linguistically reinforce users' gender stereotypes, which in turn leads to the reinforcement of systemic biases. Such biases have become a concern for civil rights and feminist scholars and activists (Islam et al., 2021). This intersectional approach combines

humanities perspectives with AI technology to explore how AI is demonstrating gender bias, stereotypes, and age discrimination, which exacerbates existing inequality.

### *2.2. AI Bias & Discrimination*

The term bias is used in this thesis to refer to outcomes of computer systems that systematically and unfairly discriminate against certain individuals or groups of individuals in favour of others (Castaneda et al., 2022). Friedman and Nissenbaum (1996) categorise bias into three types: pre-existing bias, technical bias, and emergent bias. People can experience these biases in various AI technologies. Pre-bias refers to the bias that exists before the development and implementation of a computer system. For example, the NLP model tends to associate verbs with males (e.g., fight, overpower) and combines adjectives and adverbs with females (e.g., giving, emotionally), as these are established patterns in human language use (Caliskan, 2023). Technical bias arises from problem-solving in technical design. For instance, Facial recognition systems use white male pictures as the study database. As a result, white men can be better recognised than women or people from other ethnicities (Castaneda et al., 2022). Emergent bias arises only in the context of use, usually sometime after a design is completed. For example, a decision-making system designed solely for Asian women is used for global analysis, which can lead to bias (Friedman & Nissenbaum, 1996).

In the image generation systems, the pictures it generates often exhibit significant stereotypes. For example, the system combines technical occupations with males, such as professors, engineers, developers, and doctors. At the same time, women's profiles show a higher prevalence in service occupations, including teachers, nurses, and housewives (Bhandari, 2023; Garcí-a-Ull & Melero-Lázaro, 2023). Moreover, image generation systems also prefer to connect women's images with porn and sexual content, as was discovered when researchers tried to filter out erotic content and found that systems generated fewer women's images in general (Gorska & Jemielniak, 2023; Sandoval-Martin & Martínez-Sanzo, 2024). The various forms of bias and discrimination identified in image generation systems can lead to a loss of public trust, plus their embodiment adds the risk of causing irreversible physical harm (Hundt et al., 2022). These biases and discrimination have rightly captured the attention of the wider public, regulatory bodies, and researchers (Manyika, 2022). Systemic bias has long been a concern for civil rights and feminist scholars and activists (Islam et al., 2021). Hence, there is an urgency to explore this issue in relation to AI technologies and their societal impacts. This paper will specifically address gender bias and discrimination.

Stereotypes, bias, and discrimination have been extensively documented in AI technologies (Hundt et al., 2022). While studying how gender biases are presented, scholars also explore the causes of these biases, enabling them to better understand how to avoid them. Most scholars mentioned three primary factors that cause bias issues.

First, the way AI systems are created embeds and perpetuates historical inequalities. This issue has been largely discussed in relation to AI training with unbalanced datasets, including non-representative sampling, imbalanced sampling, incorrect labelling, and mismeasured features (Banh & Strobel, 2023; Zhu et al., 2024). For example, one of the most famous collections of databases, the UCI Machine Learning Repository, contains 10,771 records related to women and 21,790 to men (33.08% vs. 66.92%) (Castaneda et al., 2022).

Second, the developers and creators of AI technology lack diversity. Only 13% of Web 3.0 startups include women. Furthermore, only 7% of the founders of Web 3.0 startups are women. Both numbers are worse than average for startups overall (Zhu et al., 2024). Additionally, most developers and researchers in AI technology are from upper-class or highly educated backgrounds. Because that group has a lower likelihood of being affected by gender marginalisation or bias, they often do not pay attention to such issues (Hundt et al., 2022).

Third, a growing body of scholarship emphasises that social inequalities are not merely reflected in AI systems but are fundamentally embedded within the sociotechnical operations that constitute them. As Mulvin (2021) argues, AI development involves components such as databases, classification systems, and algorithmic models that encode longstanding ideological frameworks, including racial segregation and eugenic thought. Rather than treating bias as a surface-level error or misrepresentation, this perspective aligns with what Phan and Wark (2021) describe as the "crisis of representation", recognising that representations are not simply descriptive but performative and constitutive of social realities. In this view, the discriminatory effects of AI are not only due to how gender, race, or other identities are represented but also arise from the assumptions and epistemologies that structure the design and deployment of AI

technologies. (Costanza-Chock, 2020) illustrates this through the example of "Travelling while Trans," where airport security systems reproduce gender binarism and surveillance-based discrimination. In Costanza-Chock's analysis, algorithmic models embedded in body scanners classify individuals based on rigid male/female binaries, reinforcing normative ideals of the acceptable traveller. This design is not neutral. It enacts harm by marginalising non-binary and transgender individuals and upholds structural exclusion under the guise of objectivity and security enforcement. Similarly, Chun (2021) critiques the logic embedded in machine learning algorithms, which often rely on reductive associative reasoning. These seemingly benign categorisations, she argues, reflect deeper ideological assumptions rooted in eugenics and cultural essentialism. Likewise, Malevé and Sluis (2023) demonstrate how the ImageNet database embeds cultural categories, rather than representing the "real world," using the example of how different marine animals are associated with trophies (sharks) or food (lobsters). These arguments underscore that AI systems do not operate outside of culture or politics. Instead, they actively shape social hierarchies through sociotechnical constructions of normativity and deviance.

AI technologies have permeated every aspect of human life. It is clear that gender bias issues in AI technologies can potentially cause substantial societal harm, including perpetuating systemic disadvantages by reinforcing gender stereotypes and accentuating gender binaries, as well as impacting people's self-esteem, confidence, and authenticity. In turn, this may lead to increased social stigmatisation (Fosch-Villaronga et al., 2021). Researchers have demonstrated multiple systematic effects of AI gender bias.

First, it perpetuates gender stereotyping (Fosch-Villaronga et al., 2021). As Hundt et al. (2022) demonstrate in a study of voice assistant toys used to educate their children. They described how parents ask toy robots to assist their children in recognising professions, such as doctors, nurses, teachers, and police officers. The pictures displayed by the toy (male doctor, female nurse) will directly influence the child's perception of occupations in relation to gender. This indicates that when trained with a biased database, these toys instill that bias in children.

Second, AI gender bias reinforces sex binarism and exacerbates gender stereotyping. Most databases only separate gender into male and female and assign masculine features to men and feminine qualities to women, which stimulates gender structural disadvantages and systems of oppression in our society that can lead individuals from marginalised groups to perform below their true potential (Fosch-Villaronga et al., 2021; Islam et al., 2021).

Third, AI gender bias will stigmatise specific population groups and damage the fairness and equity of society (Fosch-Villaronga et al., 2021; Garcí-a-Ull & Melero-Lázaro, 2023). Women have more opportunities associated with keywords like "sexy" and "erotic." They are often presented in this form as well. It creates the illusion that women are constantly employed in the relevant industry (Sandoval-Martin & Martínez-Sanzo, 2024). For instance, in major recommendation systems, men will be more likely to be recommended for STEM majors and women for humanities majors. In contrast, in criminal justice AI systems, males have higher probabilities and longer lengths of incarceration (Blomberg et al., 2010; Islam et al., 2021). These systemic problems will continue to stimulate personal issues. Algorithms learn people's perceptions and societal biases. This can lead to a reinforcement loop that supports undesirable patterns of discrimination or outdated social norms in algorithmic decisions and, consequently, in user behaviour (i.e., users' replication of biases) and has been shown to have a prescriptive effect on people's individual practices and behaviours (Kopeinik et al., 2023).

### *2.3. China's Research Gap: Socio-Cultural Bias In Domestic Generative AI*

While scholarship on AI bias has expanded rapidly in recent years, much of the literature remains concentrated on systems developed in North America and Europe. Existing research has extensively examined how Western platforms such as DALL·E, MidJourney, and Stable Diffusion reproduce cultural stereotypes, racial inequalities, and gendered norms (Bhandari, 2023; Garcí-a-Ull & Melero-Lázaro, 2023). These studies demonstrate that image generation systems are not neutral tools but embed and amplify the social hierarchies of the contexts in which they are built. However, comparatively little attention has been paid to non-Western contexts, particularly China, despite its rapid development of generative AI technologies and their growing domestic and global influence.

Within Chinese scholarship, there is a body of work on algorithmic governance, censorship, and the political economy of platforms (Y. Huang & Cao, 2023; Qiu, 2023). Yet research specifically addressing

the socio-cultural bias of Chinese generative AI systems remains limited. Most international discussions of AI in China focus on regulatory frameworks, state–industry collaboration, or geopolitical competition (Hine, 2024; Mao, 2025; Roberts et al., 2021), leaving the cultural and ethical implications of generative outputs largely unexplored. This is a significant gap, as Chinese platforms often operate within unique ideological and social conditions that shape both data collection and model design. Moreover, feminist and critical media studies perspectives—central to analyses of algorithmic bias in Western platforms—have only recently begun to be applied to Chinese AI systems. Existing studies on gender in Chinese digital culture focus primarily on recommendation algorithms online activism, or state-mediated feminist discourse (S. Huang & Sun, 2021; Leung, 2003; Liu et al., 2013; Wu, 2005; Xu, 2009). Very few works address how generative AI, as a cultural producer, encodes gender and age hierarchies in its visual outputs. This lack of attention is particularly problematic because generative systems like Wenxinyige are not only technological artefacts but also cultural intermediaries that can reinforce patriarchal norms and reproduce unequal power relations in highly visual and socially influential ways.

Addressing this gap, the present study examines Wenxinyige as a case study of Chinese generative AI, highlighting how gender stereotypes and ageist assumptions are embedded in its outputs. By situating Wenxinyige within global debates on algorithmic justice while foregrounding its local socio-political conditions, this research contributes to a more inclusive understanding of AI ethics and digital inequalities that moves beyond Western-centric perspectives.

## 3. METHODOLOGY

This paper's case study on Image Generation Systems focuses on the AI art and creativity assistance platform Wenxinyige, designed by Baidu, the most prominent digital company in China (Jia et al., 2018). Wenxinyige enables users to generate high-quality photos and videos, including paintings that match input text descriptions and reference images in terms of direction, style, and size (Ma et al., 2024). Though Wenxinyige landed earlier than Wenxinyiyan, one of the most famous Chinese large language models, scholars seldom choose Wenxinyige as the research object. This is because Western countries' image generation systems, such as DALL·E, Midjourney, Stable Diffusion, and Adobe Firefly, have captured the Chinese market at the initial stage (Sandoval-Martin & Martínez-Sanzo, 2024). By selecting Wenxinyige as the research object, this paper will fill the academic research gap regarding the lack of research on Wenxinyige.

The study of Wenxinyige employs the walkthrough method. Simulation steps were used to explore the political, economic, and cultural meanings embedded in the Wenxinyige platform. Many scholars have previously done data collection for image generation systems, and most have analysed the ratio of men and women in the generated images and the correlation between gender and occupation by inputting different occupations (Chauhan et al., 2024; Friedrich et al., 2024; Garcí-a-Ull & Melero-Lázaro, 2023; Gorska & Jemielniak, 2023; Sandoval-Martin & Martínez-Sanzo, 2024; Wu et al., 2024). I employ a similar approach on this platform, while also building upon the work done by Wu et al. (2024), which demonstrates that the biases of image generation systems can be expressed in terms of occupation, adjectives, objects, clothing, and nationality. In order to study the correlation between occupation and gender, I also analysed gender bias and stereotypes by entering different adjectives, including appearance, personality, and behaviour.

My research methodology is divided into the following specific steps:

1. Define a range of occupational categories for input into the image generation system, using the report of the MSA: "Average Salary in China in 2025" (D. Zhou, 2025). The report breaks down occupations into 48 categories, and I selected a representative occupation from each category. I divided these 48 occupations into four categories for comparison: different occupations in the same industry, symbiotic occupations, different types of the same occupation, and different genders in the same occupation. Specific occupational classifications are shown in Table 1.

***Table 1: Occupation Of Wenxinyige Input.***

| Different occupations in the same industry (high skill; low skill) | Symbiotic occupations (leader; subordinate) | Different types of the same occupation | Different genders in the same occupation |
|---|---|---|---|
| Professor; Teacher | Boss; Secretary | Criminal Lawyer; Civil Lawyer; Divorce Lawyer | Male and Female Professor |
| Doctor; Nurse | Director; Actor | Fashion Designer; Industrial Designer; UI Designer | Male and Female Doctor |
| Captain; Attendant | Headmaster; Teacher | Oil Painting Artist; Musical Artist; Dance Artist | Male and Female Captain |
| Fireman; Social Worker | Photographer; Model | | Male and Female Lawyer |
| | | | Male and Female Nurse |
| | | | Police Officer |
| | | | Solider |
| | | | Male and Female Boss |
| | | | Male and Female Entrepreneur |
| | | | Male and Female Model |
| | | | Father; Mother |
| | | | Husband; Wife |

In order to control the variables, the prompt for all occupations was "请给我一张xx的图片 (Please generate me a picture of xx)". Four pictures were generated for each keyword, and a total of 192 images were collected. In four different classifications, I compare the ratio of men and women in various types of occupations and subordinate occupations in the same industry. I also compared the gender relationships of the same occupation in different classifications, such as criminal lawyer, fashion designer, and musical artist. Lastly, I compared the characteristics of male and female pictures in different gender classifications of the same occupation.

2. In addition to occupation, I also defined words related to appearance, personality, and action words to add to the prompts to allow me to investigate further whether Wenxinyige displayed gender stereotypes. I used a corpus tool to select positive, negative, and neutral descriptive words, respectively. To ensure gender fairness, the descriptive words for males and females were selected as evenly as possible. See Table 2 for specific vocabulary choices.

***Table 2: Wenxinyige's Appearance, Personality, And Action Words.***

| Appearance | Personality | Action |
|---|---|---|
| Strong | Decisively | Apologise |
| Elegant | Consideration | Negotiate |
| Friendly | Curiosity | Joke |
| Handsome | Confident | |
| Beautiful | Sensitivity | |
| Dignified | Kindness | |
| Tall | Fortitude | |
| Refined | Gentleness | |
| Capable | Independence | |
| Young | High-educated | |
| Elder | Laziness | |
| Obesity | Patience | |
| Fashion | Crime | |
| Experienced | Bravery | |
| | Anger | |
| | Positivity | |

Similar to the occupation input, the prompt for appearance and personality was "请给我一张xx的人图片 (Please generate me a picture of xx person)". As for the action word, the prompt was "请给我一张男人向女人xx的图片"(Please generate a picture of that man xx to/with woman). I added behaviour words with different genders to analyse the results of the generated images. Each keyword generates four images equally, and I collected a total of 172 pictures for analysis. Additionally, care was taken during the research process to prevent the sharing or dissemination of potentially harmful or discriminatory images generated by the AI system,

and all outputs were used solely for analytical purposes.

The occupation and descriptive word lists used were selected with reference to both empirical relevance and cultural applicability. Occupations were derived from the 2025 MSA salary report to ensure representativeness across industries. However, not all categories were included. Some occupations were excluded because they generated duplicate or indistinguishable results (e.g., overlapping different types of designers), while others failed Wenxinyige's internal vetting and thus could not be used consistently. For example, police, soldiers, and lawyers, Wenxinyige is unable to return results with female images or it outputs images of masculine women. Similarly, for descriptive terms, the initial list was derived from corpus-based frequency analysis of Chinese adjectives and verbs associated with appearance, personality, and behaviour. Both positive and negative descriptors were considered to capture a wide spectrum of social evaluations. Although I defined negative options, I cannot use them extensively because Wenxinyige has a strict vetting algorithm, and most negative descriptors were largely excluded due to the system's censorship filters, which prevented image generation. This exclusion reflects not only technical limitations but also the normative assumptions embedded in the system: the platform implicitly restricts overtly stigmatising descriptors while allowing more subtle forms of gendered stereotyping to persist.

Cultural and linguistic factors also influenced the final keyword selection. Prompts were written in simplified Chinese, considering that some common occupations in Chinese already carry implicit gender associations, such as "空姐(female flight attendant)". I paid attention to these and tried to replace them with a more neutral appellation. For instance, "空姐 (female flight attendant)" is replaced by "空乘人员 (flight attendant)". In addition, unlike English, many Chinese occupational nouns and adjectives are inherently gendered or carry conventional associations. For example, "护士" (nurse) is widely perceived as female-coded, while "工程师" (engineer) is male-coded in public discourse. Similarly, adjectives such as "温柔" (gentle) or "干练" (capable) evoke culturally specific ideals of femininity and masculinity. Using these terms as prompts not only mirrors the language practices of actual users but also reveals how linguistic conventions interact with algorithmic modelling to reproduce social biases.

While these choices inevitably involve subjectivity, they also highlight the socio-technical embeddedness of generative AI research. Keyword selection was not a neutral act but itself constrained by institutional, cultural, and linguistic structures. By making these processes explicit, this study acknowledges the limitations of its dataset while also demonstrating how localised language and governance frameworks shape the production of algorithmic bias. This reflexive approach underscores that examining Wenxinyige requires attending not only to technical outcomes but also to the cultural logics and power relations encoded in the very design of prompts.

## 4. RESULTS

The generated 192 images show significant occupational sexism. As Figure 1 demonstrates, jobs that require a higher level of skill and experience often feature male images, while service or less skilled jobs typically feature female images. Meanwhile, for the dominant occupation in a classification, the image generated is always male, while for the subordinate occupation, it is always female. In addition, the results also show that Wenxinyige presents significant age discrimination. Men in the images are consistently portrayed as older and more experienced, and they are always dressed in dark clothing. While women in these images are sometimes depicted in dark clothing, they typically wear bright colours and consistently appear younger and more attractive than the male figures.



***Figure 1: Comparison Of Male And Female Images.***

Pictures depicting appearance have a balanced proportion of men and women, but with apparent gender stereotypes. As Figure 2 indicates, strong and tall usually generate male images, whereas nobility and refinement usually generate female images. An interesting phenomenon is that when asked to generate character-related pictures, the pictures usually appeared as children's images. As to why this occurs, four reasons seem possible. First, Wenxinyige's training data about personality either lacks adult pictures or is dominated by children's pictures. Second, adult personalities are rarely outwardly visible, whereas images of children are more easily understood. Third, in past usage data, user requests to co-occur "personality" with children's images may have been more frequent, leading Wenxinyige to default to generating images of children displaying their personality in the absence of other instructions. However, these three conjectures are not confirmed because Wenxinyige does not make his training database publicly available. Therefore, I cannot know its exact data content, size, and filtering mechanisms.



***Figure 2: Appearance Output Of Wenxinyige.***

When it comes to behavioural keywords, it is obvious from Figure 3 that women are always presented as weak, less dominant, or passively compared with images of men. Whether a man apologises to a woman, or a woman apologises to a man, women are always politely bending over to appear humble. Even when it is established that the man makes the mistake, women are not portrayed as presenting their point of view in a strong manner. Furthermore, in the pictures of women negotiating and men negotiating, women are clearly listening. In contrast, men tend to be authoritative and often appear to be giving instructions. In the last type of joking behaviour, Wenxinyige only allows males to tell jokes to females, but not females to tell jokes to males. In addition, the images of males telling jokes to females show that both parties are having fun, with no teasing or mocking evident.



***Figure 3: Apologise: Left-Male To Female; Right-Female To Male.***

### *4.1. Discussion*

The gender differences in the generated occupational images suggest that Wenxinyige internalises and perpetuates a culturally entrenched gender hierarchy of occupational roles, where leaders are inherently male, and subordinates are female. While part of this bias may stem from imbalances in training data, where male-associated occupations are more frequently represented and female-associated ones underrepresented, Wenxinyige also reflects China's socio-cultural norms, Menke (2017) associate this aspect of Chinese culture with ancient Chinese Confucianism, which remains influential in perpetuating patriarchal power in China today, including the association of men with public and women with private spheres and men with dominance and women with subordinate positions. This notion, which continues to this day, has similarly influenced the process of semantic compression, Offert and Phan (2024) arguing that generative AI operates through semantic compression, a cultural technique for reducing complex social concepts into a space of potential features. Such outcomes illustrate two overlapping mechanisms: on the one hand, algorithmic semantic compression, which reduces complex social concepts into simplified visual features; on the other, cultural sedimentation, whereby entrenched associations in Chinese discourse, such as Wenxinyige's association of nurses with women and strong with men, are made without scrutiny. This compression process typically reconfigures dominant visual norms, perpetuating representational imbalances. Wenxinyige is thus presenting and perpetuating the generally accepted occupational gender order, which results from a combination of societal stereotypes, databases, and algorithmic bias.

In addition, this occupational bias also reflects the theory of the 'male gaze' (King, 2020; Mulvey, 2001). Mulvey suggests that traditional cinema objectifies women as objects to be viewed by placing the viewer in the position of a heterosexual male through the lens of the camera. Wenxinyige's generated images are now the new medium of the gaze, replicating and updating the traditional logic of the gaze in visual generation: occupational authority is visually encoded as male, and the system is unable to visualise female competence outside of the traditionally feminised domain. This reveals not only a continuation of the global phenomenon of the male gaze, documented in feminist film theory, but also its localisation within Chinese patriarchal visual culture. This localisation is evident in the way Wenxinyige visualises occupations and authority. For example, positions of leadership, such as "boss" or "professor, " are consistently generated as male, whereas roles coded as supportive or subordinate, such as "secretary" or "nurse," are represented as female. In visual terms, authority is masculinised and service is feminised, which reflects not only the algorithm's bias but also longstanding Chinese cultural narratives that confine women to the private or auxiliary sphere. The platform thus reproduces the male gaze by making women visible primarily as objects of beauty and care, while rendering their professional authority invisible. Thus, AI is not only a generator of images but also a defender of the symbolic gender order (Gillespie, 2018). In this context, it is no longer simply an image-generating tool, but an interface for disseminating dominant visual and social ideologies. Moreover, the more such occupationally sexist images are produced, the more they undermine women's occupational representation, exacerbate the pay gap, and leave women underrepresented in occupations with higher levels of power and prestige (Gorska & Jemielniak, 2023). Consequently, Wenxinyige not only perpetuates but also normalises occupational gender biases through algorithmic reproduction, reinforcing societal perceptions of gendered roles and contributing to the structural exclusion of women from positions of authority and influence. Therefore, Wenxinyige's age-coded gender representations not only reinforce traditional gendered perceptions of value and authority but also perpetuate the objectification of women through algorithmic design, solidifying cultural biases that privilege male experience and female appearance. Wenxinyige's occupational outputs must be understood as the result of a hybrid interplay: biases inherited from globalised training data and biases amplified by Chinese cultural traditions.

Besides occupation bias, Wenxinyige's output also demonstrates blatant age discrimination. Authority and experience are repeatedly coded as male, and attractiveness and visual pleasure are coded as female. These image outputs reiterate the gendered age norms of the heteronormative order, whereby males accumulate social value as they age, while females lose value as they age (Sontag, 1997). The association of authority with older men may reflect global patterns embedded in training corpora, where images of leaders disproportionately depict men. However, the algorithm also amplifies Chinese socio-cultural norms, where ageing is framed as a process of accruing value for men but declining worth for women. Notably, this is not random visual

output but reflects a culturally coded gender-age dyad: men "grow into" authority, while women are "consumed" in youth and beauty. In occupational terms, older men often signal experience and capability, while women, regardless of profession, are usually judged by their visual appeal. "Sexual attractiveness" is algorithmically embedded in the default output of female images, a sexist construction of temporal logic. Furthermore, this way of associating women always with visual pleasures continually reinforces the gendered construction of women as deserving of pretty simplicity, continually emphasising women's tendency to objectify, weakening female subjectivity, and becoming subordinate to men (Butler, 1999).

When women appear in images of behaviour such as apologising and negotiating, they tend to be in a submissive, passive, listening role. Men are in a controlling, authoritative position. These images do not merely reflect gender norms but materialise them in visual form. Even the act of "joking" can only be performed by men on women. This asymmetry is both symbolic and behavioural—it assumes men's verbal play is light-hearted, while women's humour is either irrelevant or unacceptable. Such a design reinforces the asymmetry of narrative control in gendered interactions. Wenxinyige encodes the gender logic of 'who can act and who is passive' in the mapping mechanism of language and images. This is not just a gender bias but a visual representation of the power of behaviour, whereby men are the commanders and instructors, and women are the listeners and receivers. This behavioural coding partly reflects the data-driven reproduction of stereotypical gender interactions, but it also draws heavily on Chinese socio-cultural expectations of women's submissiveness and men's authority in communication. According to Judith Butler's theory of gender performance (2025), gender is constructed through socially repetitive behavioural performances. In these terms, Wenxinyige's continuous representation of male authority and female submissiveness will reinforce hegemonic norms of masculinity and femininity. It's behavioural coding that weakens women reflects the platform's ideological endorsement of men's verbal sovereignty and women's acceptance of submissive roles, which reinforces society's gendered ethos of women's submissiveness and gentleness and men's authoritative strength.

Wenxinyige's findings suggest that algorithm-driven content production is not a passive reflection of cultural values but rather a mechanism for actively constructing, reinforcing, and disseminating dominant gender narratives. This coincides with the concept of "soft bootstrapping" mentioned by Butler (2025), whereby users are subtly guided to internalise normative identities and expectations, which are then repeated in their everyday and online personas (Butler, 2025). By embedding highly gendered and stereotypical content, the platform reinforces understandings of women as submissive and beautiful and men as authoritative and skilled. Repeated exposure to this content naturalises hierarchical gender roles and de-legitimises others, shaping users' perceptions of themselves and others. Women may become anxious about their self-image and become overly attached to societal expectations by striving for beauty and consistency, while men may become more obsessed with rejecting the toxic masculinity of weakness and repressed emotions. In this context, marginalised groups such as older women, feminised men, and those who do not embody these social standards of attractiveness may perceive themselves as failures and lacking in value. Research on the gender identity of social media adolescents suggests that platforms are replacing family and school in the presentation of gender roles. In the long run, platform users will gradually internalize the internet's image of what is socially expected and influence users' correct gender perceptions and identities (Ahn et al., 2022; Hundt et al., 2022). As a result, femininity will become more closely associated with being consumed, viewed, and dominated. Such content normalises existing hierarchies and gender expectations while obscuring their artificially constructed nature and even preventing the full realisation of feminist liberation. In sum, Wenxinyige's outputs are shaped by a hybrid interplay of biases: some arising from the technical architecture and globalised training data, others deeply rooted in Chinese socio-cultural norms and linguistic conventions. Distinguishing between these layers is crucial for understanding how generative AI both inherits universal algorithmic limitations and reproduces culturally specific hierarchies.

## 5. CONCLUSION

This study has demonstrated that Wenxinyige, a representative Chinese image generation system, reproduces entrenched gender stereotypes and ageist assumptions through its outputs. By encoding occupational hierarchies, privileging male authority, and portraying women as youthful, attractive, and submissive, the platform perpetuates patriarchal cultural logics under the guise of technological neutrality, exemplifying how algorithmic systems can exacerbate discrimination and digital

inequalities, particularly for women and marginalised groups. These findings highlight that generative AI is not a passive tool of visual creation but an active agent in shaping and reinforcing unequal social norms.

In addition, this paper focuses on the Chinese AI systems, expanding the largely Western-centered scholarship to include the Chinese context. This study offers a critical lens for understanding how cultural, political, and technological conditions intersect in the production of algorithmic discrimination. Ultimately, addressing bias in generative AI requires recognising these systems as socio-technical artefacts that both reflect and reproduce existing inequalities. This highlights the pressing need for more inclusive data practices, increased transparency in model design, and the incorporation of diverse perspectives in AI development. For policymakers, the findings highlight the social risks associated with generative AI and underscore the importance of safeguarding human rights and promoting digital justice. For developers and platforms, they highlight the responsibility to mitigate bias, not only to enhance fairness but also to prevent the normalisation of harmful stereotypes. In doing so, it contributes to the global conversation on how AI can be designed and governed in ways that respect human dignity, protect marginalised voices, and promote a more equitable digital future.

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## REFERENCES

Ahn, J., Kim, J., & Sung, Y. (2022). The effect of gender stereotypes on artificial intelligence recommendations. Journal of Business Research, 141, 50-59.

Banh, L., & Strobel, G. (2023). Generative artificial intelligence. Electronic Markets, 33(1), 63. https://doi.org/10.1007/s12525-023-00680-1

Bhandari, A. (2023). Bias in AI: A Comprehensive Examination of Factors and Improvement Strategies. International Journal of Computer Science and Engineering, 10(6), 9–14. https://doi.org/10.14445/23488387/IJCSE-V10I6P102

Blomberg, T., Bales, W., Mann, K., Meldrum, R., & Nedelec, J. (2010). Validation of the COMPAS risk assessment classification instrument. College of Criminology and Criminal Justice, Florida State University. https://criminology.fsu.edu/sites/g/files/upcbnu3076/files/2021-03/Validation-of-the-COMPAS-Risk-Assessment-Classification-Instrument.pdf

Borau, S. (2025). Deception, Discrimination, and Objectification: Ethical Issues of Female AI Agents: Deception, Discrimination, and Objectification: Ethical Issues of Female AI Agents. Journal of Business Ethics, 198(1), 1-19.

Butler, J. (1999). Gender Trouble: Tenth Anniversary Edition (2nd ed.). Routledge. https://doi.org/10.4324/9780203902752

Butler, J. (2025). Performative acts and gender constitution: An essay in phenomenology and feminist theory. In The performance studies reader (pp. 186-196). Routledge.

Caliskan, A. (2023). Artificial Intelligence, Bias, and Ethics. Proceedings of the Thirty-Second International Joint Conference on Artificial Intelligence, 7007–7013. https://doi.org/10.24963/ijcai.2023/799

Castaneda, J., Jover, A., Calvet, L., Yanes, S., Juan, A. A., & Sainz, M. (2022). Dealing with Gender Bias Issues in Data-Algorithmic Processes: A Social-Statistical Perspective. Algorithms, 15(9), Article 9. https://doi.org/10.3390/a15090303

Chauhan, A., Anand, T., Jauhari, T., Shah, A., Singh, R., Rajaram, A., & Vanga, R. (2024). Identifying Race and Gender Bias in Stable Diffusion AI Image Generation. 2024 IEEE 3rd International Conference on AI in

Cybersecurity (ICAIC), 1–6. https://doi.org/10.1109/ICAIC60265.2024.10433840
Chowdhury, M., & Sadek, A. w. (2012). Artificial Intelligence Applications to Critical Transportation Issues (p. 22690). Transportation Research Board. https://doi.org/10.17226/22690
Chun, W. H. K. (2021). Discriminating Data: Correlation, Neighborhoods, and the New Politics of Recognition. MIT Press.
Costanza-Chock, S. (2020). Introduction: #TravelingWhileTrans, Design Justice, and Escape from the Matrix of Domination. Design Justice. https://designjustice.mitpress.mit.edu/pub/ap8rgw5e/release/1,
Dobrev, D. (2012). A Definition of Artificial Intelligence (No. arXiv:1210.1568). arXiv. https://doi.org/10.48550/arXiv.1210.1568
Fosch-Villaronga, E., Poulsen, A., Søraa, R. A., & Custers, B. H. M. (2021). A little bird told me your gender: Gender inferences in social media. Information Processing & Management, 58(3), 102541. https://doi.org/10.1016/j.ipm.2021.102541
Friedman, B., & Nissenbaum, H. (1996). Bias in computer systems. ACM Trans. Inf. Syst., 14(3), 330–347. https://doi.org/10.1145/230538.230561
Friedrich, F., Brack, M., Struppek, L., Hintersdorf, D., Schramowski, P., Luccioni, S., & Kersting, K. (2025). Auditing and instructing text-to-image generation models on fairness. AI and Ethics, 5(3), 2103-2123. https://doi.org/10.1007/s43681-024-00531-5
Garcí-a-Ull, F.-J., & Melero-Lázaro, M. (2023). Gender stereotypes in AI-generated images. Profesional de la información, 32(5), Article 5. https://doi.org/10.3145/epi.2023.sep.05
Gillespie, T. (2018). Custodians of the Internet: Platforms, Content Moderation, and the Hidden Decisions That Shape Social Media. Yale University Press.
Gorska, A. M., & Jemielniak, D. (2023). The invisible women: Uncovering gender bias in AI-generated images of professionals. Feminist Media Studies, 23(8), 4370–4375. https://doi.org/10.1080/14680777.2023.2263659
Hine, E. (2024). Governing Silicon Valley and Shenzhen: Assessing a New Era of Artificial Intelligence Governance in the United States and China. Digital Society, 3(3), 50. https://doi.org/10.1007/s44206-024-00138-7
Huang, S., & Sun, W. (2021). # Metoo in China: Transnational feminist politics in the Chinese context. Feminist Media Studies, 21(4), 677-681. https://www-tandfonline-com.virtual.anu.edu.au/doi/full/10.1080/14680777.2021.1919730
Huang, Y., & Cao, X. (2023). Calling on the Third-party Privacy Control into Algorithmic Governance Framework: Linking Users' Presumed Influence with Control Agency Theory. International Journal of Public Opinion Research, 35(4), edad036. https://doi.org/10.1093/ijpor/edad036
Hundt, A., Agnew, W., Zeng, V., Kacianka, S., & Gombolay, M. (2022). Robots Enact Malignant Stereotypes. 2022 ACM Conference on Fairness, Accountability, and Transparency, 743–756. https://doi.org/10.1145/3531146.3533138
Islam, R., Keya, K. N., Zeng, Z., Pan, S., & Foulds, J. (2021). Debiasing Career Recommendations with Neural Fair Collaborative Filtering. Proceedings of the Web Conference 2021, 3779–3790. https://doi.org/10.1145/3442381.3449904
Jia, K., Kenney, M., Mattila, J., & Seppala, T. (2018). The Application of Artificial Intelligence at Chinese Digital Platform Giants: Baidu, Alibaba and Tencent (SSRN Scholarly Paper No. 3154038). https://doi.org/10.2139/ssrn.3154038
Kazim, E., & Koshiyama, A. S. (2021, September 10). A high-level overview of AI ethics: Patterns, 2(9). https://www.cell.com/patterns/fulltext/S2666-3899(21)00157-4
King, C. S. (2020). The male gaze in visual culture. In The Routledge handbook of gender and communication (pp. 120-132). Routledge.
Kopeinik, S., Mara, M., Ratz, L., Krieg, K., Schedl, M., & Rekabsaz, N. (2023). Show me a "Male Nurse"! How Gender Bias is Reflected in the Query Formulation of Search Engine Users. Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems, 1–15. https://doi.org/10.1145/3544548.3580863
Leung, A. S. M. (2003). Feminism in Transition: Chinese Culture, Ideology and the Development of the Women's Movement in China. Asia Pacific Journal of Management, 20(3), 359–374. https://doi.org/10.1023/A:1024049516797
Liu, L. H., Karl, R. E., & Ko, D. (2013). The Birth of Chinese Feminism: Essential Texts in Transnational Theory. Columbia University Press.

MA S, WANG B Y, LI S J (2024). Designing elderly-friendly cities based on a generative large language model: A case study of streets in Hangzhou[J]. Journal of Human Settlements in West China, 39(2): 28-34.

Malevé, N., & Sluis, K. (2023). The Photographic Pipeline of Machine Vision; or, Machine Vision's Latent Photographic Theory. Critical AI, 1(1–2). https://doi.org/10.1215/2834703X-10734066

Manyika, J. (2022). Getting AI Right: Introductory Notes on AI & Society. Daedalus, 151(2), 5–27. https://doi.org/10.1162/daed_e_01897

Mao, Y. (2025). Artificial Intelligence Governance Made in China: Negotiating Imaginaries and Power. Technology, Power and Society: Critical Perspectives on the Global Digital Transformation, 1, 184.

Menke, A. (2017). The Development of Feminism in China.

Mohajan, H. K. (2022). Four Waves of Feminism: A Blessing for Global Humanity. Studies in Social Science & Humanities, 1(2). https://doi.org/10.56397/SSSH.2022.09.01

Mulvey, L. (2001). Unmasking the gaze: some thoughts on new feminist film theory and history. Lectora (Barcelona), (7), 0005-14.

Mulvin, D. (2021). Proxies: The Cultural Work of Standing In. MIT Press.

Offert, F., & Phan, T. (2024). A sign that spells: Machinic concepts and the racial politics of generative AI. Journal of Digital Social Research, 6(4), Article 4. https://doi.org/10.33621/jdsr.v6i440462

Phan, T., & Wark, S. (2021). Racial formations as data formations. Big Data & Society, 8(2), 20539517211046377. https://doi.org/10.1177/20539517211046377

Qiu, J. L. (2023). The Return of Billiard Balls? US–China Tech War and China's State-Directed Digital Capitalism. Javnost - The Public, 30(2), 197–217. https://doi.org/10.1080/13183222.2023.2200695

Roberts, H., Cowls, J., Morley, J., Taddeo, M., Wang, V., & Floridi, L. (2021). The Chinese approach to artificial intelligence: an analysis of policy, ethics, and regulation. In Ethics, governance, and policies in artificial intelligence (pp. 47-79). Cham: Springer International Publishing. https://link.springer.com/chapter/10.1007/978-3-030-81907-1_5

Sandoval-Martin, T., & Martínez-Sanzo, E. (2024). Perpetuation of Gender Bias in Visual Representation of Professions in the Generative AI Tools DALL·E and Bing Image Creator. Social Sciences, 13(5), Article 5. https://doi.org/10.3390/socsci13050250

Sontag, S. (2018). The double standard of aging. In The other within us (pp. 19-24). Routledge.

Stahl, B. C. (2021). Ethical Issues of AI. In B. C. Stahl (Ed.), Artificial Intelligence for a Better Future: An Ecosystem Perspective on the Ethics of AI and Emerging Digital Technologies (pp. 35–53). Springer International Publishing. https://doi.org/10.1007/978-3-030-69978-9_4

Waisi, M. (2020). Advantages and Disadvantages of AI- based Trading and Investing Versus Traditional Methods. 4–5.

Wang, P. (2019). On Defining Artificial Intelligence. Journal of Artificial General Intelligence, 10(2), 1–37. https://doi.org/10.2478/jagi-2019-0002

Wu, Y. (2005). Making Sense in Chinese "Feminism"/Women's Studies. In M. Waller & S. Marcos (Eds.), Dialogue and Difference: Feminisms Challenge Globalization (pp. 29–52). Palgrave Macmillan US. https://doi.org/10.1007/978-1-137-07883-4_2

Wu, Y., Nakashima, Y., & Garcia, N. (2024, October). Stable diffusion exposed: Gender bias from prompt to image. In Proceedings of the AAAI/ACM conference on AI, ethics, and society (Vol. 7, pp. 1648-1659).

Xu, F. (2009). Chinese feminisms encounter international feminisms: Identity, power and knowledge production. International Feminist Journal of Politics, 11(2), 196-215. https://www-tandfonline-com.virtual.anu.edu.au/doi/full/10.1080/14616740902789567#d1e223

Zhang, Q., Lu, J., & Jin, Y. (2021). Artificial intelligence in recommender systems. Complex & Intelligent Systems, 7(1), 439–457. https://doi.org/10.1007/s40747-020-00212-w

Zhou, D. (2025, March 20). Average Salary in China for 2025 [Expert Guide]. https://msadvisory.com/average-salary-in-china/

Zhou, X., Xu, Y., Li, Y., Josang, A., & Cox, C. (2012). The state-of-the-art in personalized recommender systems for social networking. Artificial Intelligence Review, 37(2), 119–132. https://doi.org/10.1007/s10462-011-9222-1

Zhu, J., Li, F., & Chen, J. (2024). A survey of blockchain, artificial intelligence, and edge computing for Web 3.0. Computer Science Review, 54, 100667. https://doi.org/10.1016/j.cosrev.2024.100667