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Gender Representation in Generative AI Image Creation and Adolescents' Emotional Responses: A Dual Perspective from Semiotics and Affective Computing

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SUMMARY: *In recent years, with the widespread use of generative artificial intelligence image technology by young people, numerous examples have emerged of these images being employed to convey emotions and gender identity through visual symbols. Using both semiotics and affective computing, this study will conduct content analysis, experimental research and in-depth interviews to explore the symbolic encoding features of gender representation in AI-generated images and adolescents' emotional responses, as well as their underlying connections. Based on the above results, both traditional gender stereotypes in terms of clothing, posture and environment are still visible; at the same time, technology is also creating various forms of gender expression. Adolescents' Emotional Responses to Stereotypic and Pluralistic Representations: Cognitive Conformity vs. Curiosity/Identification. Collect physiological and psychological data on young people using affective computing technology to provide objective support for studying the impact of gender symbols on them. Combine semiotic analysis and affective computing to build a new research system for exploring how gender cognition develops in AI environments; at the same time, provide theoretical support and practical suggestions for regulating the creation of AI images and promoting the healthy emotional growth of adolescents.*

KEYWORDS: *Generative AI images; Gender Representation; Adolescents; Emotional Response; Semiotics; Affective Computing*

1 Introduction

1.1 Research background

Generative Artificial Intelligence (AI) image technology in the present day is based on various advanced structures, including but not limited to Generative Adversarial Networks (GANs) and Diffusion Models, and is now quite advanced. It has good efficiency and versatility, so now many places in society have been implementing this technology to construct their own social-media-based and other digital platforms. Therefore, it has become necessary for young people today, who are the "digital natives", to access information, present themselves to others and participate in society.

Although the AI-generated pictures are close to reality, they are not simply accurate copies;

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rather, they are complex algorithms based on the learning and generation of large amounts of frequent and uneven visual data. The above images are symbolic products that have been generated by combining algorithmic logic with historical data biases and deeply rooted socio-cultural structures. By means of strategic encoding and large-scale dissemination of visual symbols, these gender representations continuously affect the emotional states of young people. In turn, this will change the development of their gender identities, values and behaviour.

At present, scholars have paid more and more attention to the ethical and social problems associated with gender representation in generative AI. At one end of the spectrum is a tendency for algorithms to be based on historical data repositories and thus further entrench traditional gender stereotypes. For example, women are often depicted as being preoccupied with their looks and home life, while men are frequently shown as strong men, the heads of the family and employers in modern society. At the same time, this technology has been released publicly and generated multiple instances of various gender expressions; consequently, the single route for "gender" in traditional media has started to fragment.

Teenagers are in a sensitive stage of cognitive and emotional development for gender relations, and their systems for managing emotions are still developing; they are also more receptive to visual stimulation. This group of people is more likely to be swayed by the emotional appeal and ideology of AI-generated gender symbols due to a lack of critical thinking. Therefore, all-encompassing studies of the symbolic attributes of gender representation in generative AI, the resulting emotional responses of adolescents, and the underlying interaction mechanisms between them have significant theoretical and practical value.

1.2 Research Significance

The first three types of theoretical contributions of this paper are presented below. First, it has built a joint research system for semiotics and affective computing, broken out of the constraints of single-discipline research, and provided new research methods for gender representation and emotional response. Semiotics is applied to analyze the symbolic coding system and cultural meanings in gender representation in AI-generated images, and affective computing quantifies adolescents' emotional responses. Together, they can help us learn about how gender roles affect the feelings of young people. Second, it has added to the theoretical system of gender communication research in generative AI by clarifying the relationships among algorithms, symbols and emotions, and extended the scope of media gender studies. Third, expand research on the emotional development of adolescents and the impact of media, investigate the specific pathways through which AI-generated images affect adolescents' emotional cognition, and offer empirical support for theoretical construction in this area[2].

Several applications of this study have been realized in practice. The results of this study on gender-representation symbolisation in the AI-generated image industry can be applied to algorithm optimisation and content normalisation to produce diverse gender representations. Educational authorities and parents can use the identified patterns of emotional changes in adolescents to plan gender education and media literacy courses to help teenagers better distinguish between gender symbols and regulate their emotions. Based on the above results, the authorities will issue relevant regulations on AI-generated image content and address gender bias in the information era.

1.3 Research Methods

This study has used a multi-dimensional and in-depth way to conduct research, and the results will be presented in the following manner:

Content Analysis Method: A relatively large number of about 1,000 gender-balanced images were obtained from popular AI platforms, such as Midjourney, Stable Diffusion and DALL·E. Based on semiotics, these four types of symbols were extracted from all images: clothes (colour, style and exposure), posture (body language, dominance/submission cues), setting (home or work environment), and facial expressions (emotional mood and intensity). The generated data were analysed statistically to determine how often and in what proportion certain gendered archetypes occurred.

Experimentation: A control-group, 12-to-18-year-old adolescents were chosen as the experimental subjects (n=300). Stratified random sampling was used to recruit participants, and they were randomly assigned to one of two groups: an experimental group that saw AI images with explicit gendered symbolic representations, and a control group that saw images without gendered cues. A high-end affective computing device was used to obtain rich physiological data, such as heart rate variability (HRV), skin conductance level (SCL) and respiratory rate (RR). In addition to the above objective data, the participants' subjective emotions were also recorded by the PAD (Pleasure, Arousal, Dominance) scale and a customised questionnaire.

In-depth interview method: To learn the reasons for the change in attitude at an individual level, 60 participants from the experimental group were selected for semi-structured in-depth interviews. These sessions investigated the participants' internal cognitive processes for AI-generated gender symbols, the cultural or personal reasons for their emotional responses, and their sense of a long-term impact on their own ideas of gender.

Overall data analysis: SPSS is used for descriptions and correlations of the data, and regression analysis is carried out to find any significant patterns in the physiological and survey data. AMOS (Analysis of Moment Structures) is used to build a structural equation model (SEM) additionally. Therefore, this study will investigate how symbolic features of images are linked with adolescents' cognitive evaluations and, finally, with emotional reactions through grounded-theory coding of qualitative interview data.

1.4 Literature Review

Most current research on generative AI image creation has focused on the technical optimisation, application scenarios and ethical risks. Chen Zexuan's study of image semiotics indicates a "symbolic gap" in AI-generated paintings and thus offers a new way to understand the deficit of gender representation[3]. Although previous studies have shown that there are still gender stereotypes in the media at all times and in various parts of the world, research on generative AI images is still in its infancy. Ren Xuan's analysis of visual symbols in the animated films of New Guofeng and Dai Yijun's study on the transmission of artifact imagery provide methodological references for deconstructing the signifier and signified in AI-generated gender symbols[4, 5]. Research on adolescent emotional responses and media influence has mainly employed the old way. Xiong Liang has used affective computing technology to measure the emotions of young people objectively[6]. Jiang Haiqing, Huang Weishi and Jiang Nan have explored the semiotics of emotional communication and affective design to further illuminate the link between symbols in gender representation and emotions among adolescents [7, 8]. Overall, more in-depth research is needed on how to apply semiotics and affective computing to study the generation of AI gender representations and the corresponding emotional reactions of young people.

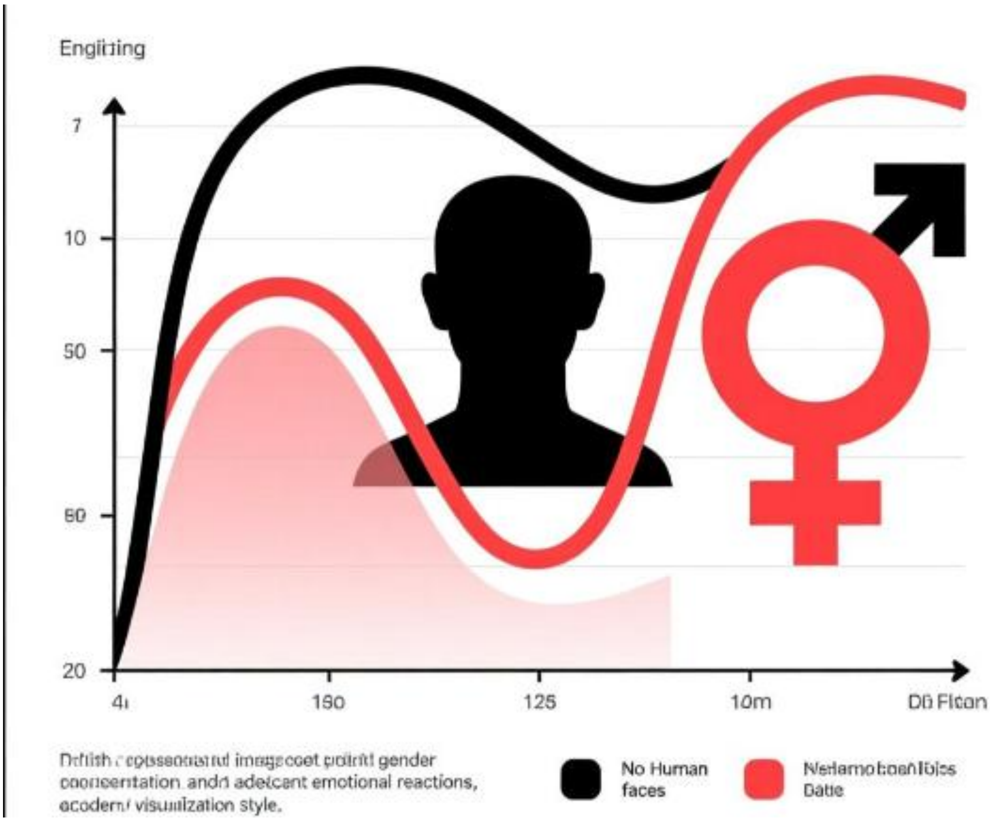

Figure 1: Lack of fusion between semiotics and emotion computing in TLNE; Study of generative AI image gender representation and copyright issues.

2 Semiotics of Gender Representation in Generative AI Images

2.1 Construction of the Semiotic Analysis Framework

Based on Saussure's structuralist semiotics and Barthes' myth theory, this paper builds a semiotic system for analysing gender representation in generative AI-generated images. Saussure proposed that signs are composed of signifiers and signifieds, and their relationship is arbitrary and conventional. Barthes built on the previous work to introduce the mythologisation process of symbols, making the original meaning appear natural and thus concealing hidden ideology and power structures. Based on the visual characteristics of AI-generated images, the four symbolic categories of gender representation in this study are clothing symbols, posture symbols, scene symbols and facial expression symbols. Both have signs and meanings: The specific visual characteristics (e.g., colours and styles of clothes, gestures and body language) are the signs, and they carry different connotations, such as "masculinity" for men's clothes and "femininity" for how women hold themselves. Mythological analysis has identified the gender ideologies in these symbols, and this study examines how traditional gender stereotypes are naturalised and authorised by AI-generated images.

2.2 Symbolic Coding Features of Gender Representation

Content analysis of 1,000 AI-generated image samples shows that generative AI images have a dual-coding pattern, and gender representation occurs simultaneously with both symbolic rigidity and diversified breakthroughs.

In terms of clothing semiotics, men's clothes are usually dark in colour (black, navy or grey) approximately 68% of the time, and are generally practical suits that convey a sense of masculinity. Female clothing mainly uses light colours (white, pink, blue) to a large extent of 72 per cent, and many of these dresses are both feminine and alluring. The encoding of traditional gender stereotypes continues to exist, and semiotics is strictly associated with "masculinity" and "femininity". However, about 15% of female images use dark colours and androgynous styles, while approximately 12% of male images are light in colour and have a feminine design; these show links to the idea of "gender equality" and deviate from traditional norms. Posture semiotics: Most men are in an upright-standing posture (75%) and appear confident, whereas most women are in a slightly slanted position (69%) and appear submissive. Pose encoding reinforces the old power dynamics of men and women. However, in some AI-generated images, about 20% of the female figures are assertive in posture and 18% of the male figures are gentle in pose; thus, the power relations of gender and semiotics have been altered towards "gender equality".

At the level of signifier for scene symbolism, men are more often seen in public areas such as workplaces (71%), which signifies "male-dominated public spheres", and women are more frequently in private or consumer spaces, such as homes (67%), representing "female-dominated private domains". This scene coding continues to maintain traditional gender role spatial divisions. However, about 22 per cent of women are shown in traditionally male-dominated public places, and 19 per cent of men in traditionally female-dominated private places, with signifiers from different gender role areas mixed, and the signifiers shifting towards "gender role diversity". At the level of emoticon coding, males mainly use neutral expressions (73%) and are thus "masculinely emotionally reserved", while females are more likely to be shown in joyful or gentle expressions (76%) and therefore "femininely emotionally expressive". This emoticon coding reflects the norms of traditional gender culture for emotional expression. Approximately 17% of men show emotionally expressive facial expressions, while 16% of women are in a neutral state; signifiers do not conform to gender norms in emotional expression and are moving towards "gender-neutral emotional expression".

2.3 The Process of Mythologization of Gender Representation

Barthes suggested in his discussion of the symbolic coding of gender representation in generative AI images that there is no objectivity, but rather a process of mythologisation. Traditional gender stereotypes are normalised as "reasonable gender differences" through the signifier-signified relationship of visual symbols, thereby obscuring the underlying ideology and power dynamics. Female figures in AI-generated images are mostly dressed in light colours and have soft bodies. Although these symbols represent "women's external expressions", their mythologized connotations are actually the "innate grace and docility of women". Thus, a change in socially constructed gender ideas has been made to reinforce gender inequality.

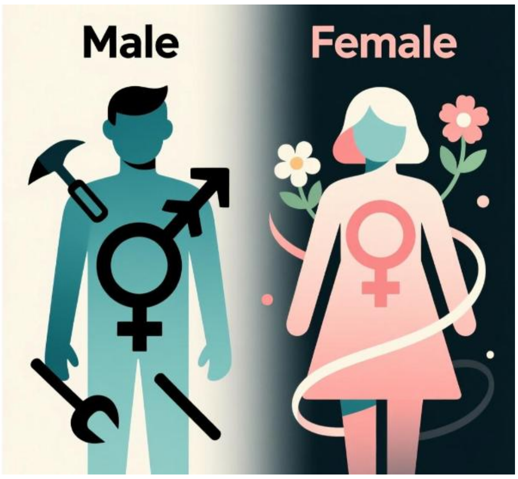

Figure 2: Symbolic representation of gender in generative AI images

Free from the old system of gender signs, it has made new myths by breaking away from the old ones. The dark clothes and relatively low positions of the women are shown both externally as "women's outward expressions" and internally as "women's equal rights and abilities with men"; thus, gender equality is naturalised as a "reasonable gender status" to promote gender awareness. Algorithms are to be employed for the myths in this way. Analysts and constructors of historical data may have reinforced the old idea of gender, or they may have created a new one by processing data and making other interventions.

3 Adolescents' Emotional Responses to AI-Generated Gendered Image Representations: An Affective Computing-Based Empirical Study.

3.1 Experimental Design and Data Collection

3.1.1 All-encompassing Experimental Design and Data Collection Method

To enhance the strength of the empirical foundation, 300 adolescent subjects aged 12-18 with different educational backgrounds were recruited via a stratified cluster random sampling method in this study. The two sexes in this cohort were equal, with 150 men and 150 women. Educationally, 100 junior high school students and 200 senior high school students were selected as the sample to study emotional responses at different stages of development. Strict inclusion criteria were set: all participants had to have documented prior experience using generative AI image platforms (e.g., Midjourney, Stable Diffusion), had normal or corrected-to-normal visual acuity, and had no clinical history of psychological disorders, cognitive deficits, or physiological impairments that could affect affective computing indicators.

The 60 high-quality AI-generated pictures served as visual aids to isolate the factor of gender representation as the independent variable. The three types of these pictures were arranged in a row.

Stereotypical Representation Group (20 images): Depicting very traditional and rigid gender roles (e.g., passive women with soft art; dominant men with strong art).

Diverse/Multicultural Representation Group (20 images): Non-traditional and boundary-breaking gender symbols (e.g., androgynous styling, reversed gender-role scenarios, and various occupational contexts).

Neutral Representation Group (20 images): A control baseline containing fundamentally gender-ambiguous or entirely neutral visual symbols.

To avoid the confounding effect of confounding variables on physiological arousal, all 60 images were normalised by image processing software to ensure that the visual characteristics, such as resolution, colour saturation, luminosity and contrast ratio, were uniform.

Collect all of participants' physiological data continuously with an advanced multi-channel biosensor. The three tracked physiological indicators are heart rate (HR), skin conductance (SC) and respiration rate (RR); all of them can be changed by emotion, cognition or a general state of arousal in the body. To supplement the above objective physiological indicators, a brief Pleasure-Arousal-Dominance (PAD) scale for self-reported emotional conditions was also used. The values of P, A and D for the three factors are all between 1 and 9; a higher number indicates a stronger emotional reaction. In addition, a self-compiled "Adolescent Gender Perception Questionnaire" was used to assess the baseline level of gender equality awareness, attitude towards gender roles, and behaviour in the participants' lives for further correlation analysis.

Before the main empirical research, a small-scale pre-experiment involving 30 randomly selected adolescents was carried out. At this time, we also tested whether the stimulus materials worked and how well the experiment was going overall. Based on the pre-experiment results, small modifications were made to the expression of the questionnaires to ensure their understanding by young people.

First, the participants filled out the demographic and gender perception questionnaires at the beginning of the laboratory class. Then, the physiological sensors were attached to them, and they were placed in a quiet room for five minutes to obtain a normal physiological reference value. To remove the differences in physiological baseline among the adolescent subjects, all raw physiological data were maximum-minimum normalised before statistics were performed. The above is the transformation:

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{1}$$

where X represents the raw physiological data point for a specific subject, and X_{min} and X_{max} denote the absolute minimum and maximum values recorded for that specific physiological metric during the entire experimental session for that individual.

The 60 experimental stimuli were shown on a high-definition monitor in a random order to avoid order effects. Each image was shown for 30 seconds, and the physiological data at baseline were recorded before and after displaying the image. After displaying each picture, show a screen with the PAD emotion scale and have participants rate the emotions in that picture based on their own experience. A 60-picture set was obtained; these were carefully removed from the sensors, and the participants were asked to rest and debrief for five minutes. After carefully filtering out the anomalous data sets (such as those with extreme sensor noise, erratic heart rate fluctuations due to physical movement, or incomplete survey submissions), a total of 286 valid data sets were finally used for statistical analysis.

3.2 General Features of Emotional Responses in Adolescence

All-encompassing descriptive and inferential statistics of the normalised physiological data showed that adolescents responded in highly varied ways, both physically and emotionally, to different paradigms of AI-generated gender representation.

Table 1: Mean Physiological Responses of Adolescents to Gender Representations (N=286)

Physiological Index	Stereotypic Representation Group	Diverse Representation Group	Neutral Representation Group	F-value	p-value
Heart Rate (HR, bpm)	78.62 ± 8.35	82.45 ± 9.12	76.33 ± 7.98	15.72	0.000
Skin Conductance (SC, μS)	3.21 ± 1.05	4.12 ± 1.23	2.98 ± 0.98	23.45	0.000
Respiratory Rate (RR, breaths/min)	16.83 ± 2.15	18.26 ± 2.34	16.25 ± 2.03	12.87	0.000

As shown in Table 1, the mean values for Heart Rate, Skin Conductance and Respiratory Rate in the Diverse Representation Group were significantly higher than those in both the Stereotypical and Neutral groups ($p < 0.001$). The above healthy response suggests that adolescents' autonomous nervous systems are more easily activated by non-traditional and diverse representations of gender. The newness and cognitive dissonance of these progressive symbols are likely to require more cognitive processing, thus inducing a stronger physiological response. The Stereotypical Representation Group had a slight increase in physiological indicators over the Neutral Group, but it was not statistically significant. Therefore, although the traditional gender stereotype still arouses an emotional response to some extent, its repeated exposure in daily life has reduced the impact on young people; thus, different kinds of social groups now attract much more attention.

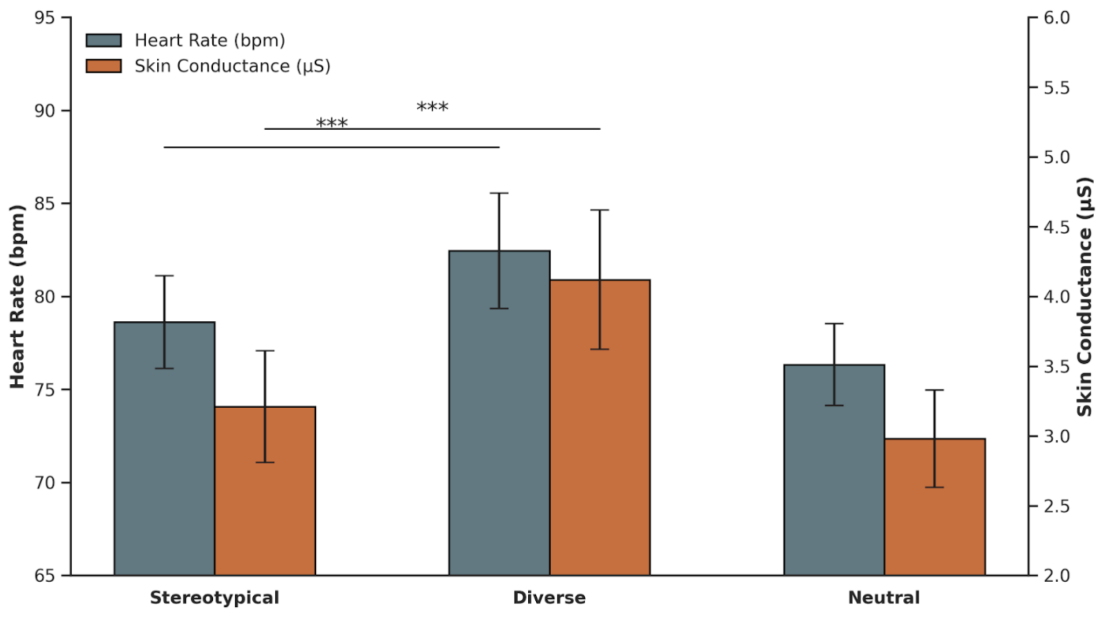

Figure 3: Bar Chart Comparing Mean Physiological Indicators (Heart Rate and Skin Conductance) in Different Gender Representation Groups

To quantify the subjective emotional responses captured by the PAD scale, we calculated the overall emotional reaction intensity by determining the spatial Euclidean distance (Emotional Distance, E) between the subjects' reported emotional states and a predefined neutral baseline within the three-dimensional PAD space:

$$E = \sqrt{(P - P_0)^2 + (A - A_0)^2 + (D - D_0)^2} \quad (2)$$

where $P, A,$ and D correspond to the subject's scores on the Pleasure, Arousal, and Dominance dimensions after viewing a specific image stimulus, respectively, while $P_0, A_0,$ and D_0 represent the standardized neutral baseline coordinates. The analysis of this subjective data corroborates the physiological findings.

Table 2: Mean of Subjective Emotional Responses of Adolescents to Gender Representations (N=286)

Emotional Dimension	Stereotypic Representation Group	Diverse Representation Group	Neutral Representation Group	F-value	p-value
Pleasure (P)	5.32 ± 1.25	6.87 ± 1.34	4.98 ± 1.12	32.67	0.000
Arousal (A)	5.15 ± 1.32	7.23 ± 1.45	4.86 ± 1.09	45.89	0.000
Dominance (D)	5.28 ± 1.21	6.54 ± 1.36	5.03 ± 1.15	28.76	0.000

Table 2 shows that the mean scores of Pleasure, Arousal and Dominance for the Diverse Representation Group were significantly higher than those in the other cohorts ($p < 0.001$). This shows that the concept of "diverse gender representation" for young people has changed; nowadays, these young people are more likely to experience strong positive emotions by encountering diverse gender roles in their media consumption. They are more likely to feel a sense of happiness and self-realisation (dominance) when viewing AI pictures that deviate from the traditional gender roles. Although the Stereotypical Group had a relatively higher subjective score than the Neutral Group ($p < 0.05$), indicating that some were passively emotionally aligned with familiar cultural norms, the degree of such identification was significantly lower than that of the enthusiastic reception of pluralistic imagery.

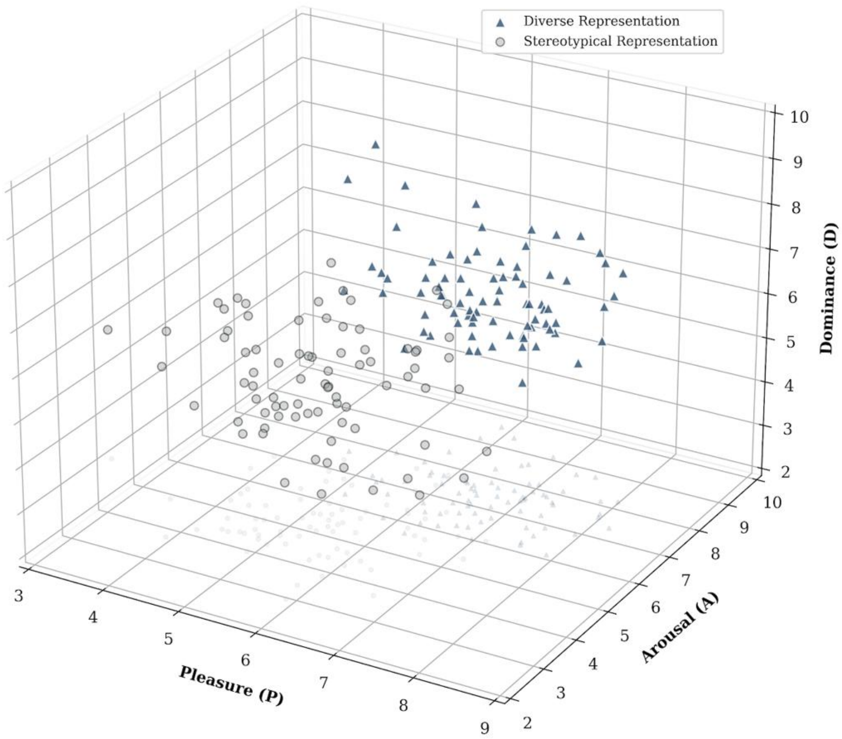

Figure 4: 3D Scatter Plot of Spatial Distribution of Adolescents' Subjective Emotions (PAD) towards Various Genders' Representations.

3.3 Different Emotional Reactions Based on Demographic Factors

In order to study in more detail what kinds of emotions these people have experienced, an independent samples t-test was conducted to determine whether the two biological sexes showed different levels of perception of AI-generated gender representations. Based on the above analysis, there are two groups.

Table 3: Gender Differences in Emotional Responses of Adolescents (N=286)

Emotion Indicators	Male Students (n=143)	Female Students (n=143)	t-value	p-value
Heart Rate (HR)	77.89 ± 8.12	81.34 ± 8.56	-3.21	0.002
Skin Conductance (SC)	3.32 ± 1.08	3.98 ± 1.15	-4.56	0.000
Pleasure (P)	5.67 ± 1.23	6.54 ± 1.31	-5.89	0.000
Arousal (A)	5.56 ± 1.30	6.87 ± 1.38	-7.23	0.000
Dominance (D)	5.78 ± 1.25	6.23 ± 1.30	-3.12	0.003

As shown in Table 3, female adolescents had consistently and significantly higher mean values in both objective physiological indicators (Heart Rate and Skin Conductance) and subjective psychological dimensions (Pleasure, Arousal, Dominance) compared with their male peers ($p < 0.05$ for all indices). Based on the above data, it is clear that young women are more sensitive to, and react differently with, gender-themed works produced by artificial intelligence.

Detailed divisions show that the paths for recognition are different. Male participants had a significantly greater degree of emotional comfort and identification with Stereotypical Gender Representations ($p < 0.05$), which was probably due to traditionalisation of socialisation and a hidden alignment with patriarchal visual dividends. On the other hand, female adolescents showed a much stronger and statistically significant positive association with Diverse Gender Portrayals ($p < 0.001$). AI-generated pictures that break away from the mould and show all kinds of strong and well-rounded women can make young girls feel good, give them a sense of self-esteem, and make them feel empowered.

4 Contemporary Inheritance of Chinese Traditional Art and Reflections on Chinese National Vocal Music

4.1 Correlation Analysis

As shown in the results of the correlation analysis in Table 5, Pearson correlation coefficients were used to examine how different symbolic coding indicators and emotional response indicators relate to one another, and what kind of association exists among gender-representing symbolic features and adolescent emotions.

Table 4: Correlation between gender-representing symbolic features and adolescents' emotional responses (N=286).

Symbol Features	heart rate (HR)	Skin conductivity (SC)	Pleasure (P)	awaken (A)	dominance (D)
Multiple clothing symbols	0.45	0.52	0.63	0.68	0.59
Multimodal Symbol	0.42	0.49	0.61	0.65	0.56
Multi-scene symbols	0.38	0.45	0.58	0.62	0.53
Multiple Emojis	0.35	0.41	0.55	0.59	0.50
Stylish clothing symbol	0.21	0.25	0.32	0.30	0.28
Stiff posture symbol	0.19	0.23	0.29	0.27	0.25
Stereotypical scene symbol	0.17	0.21	0.26	0.24	0.22
Stiff emoji	0.15	0.19	0.23	0.21	0.19

As shown in Table 4, the symbolic features of gender-inclusive representations (clothing, posture, setting, facial expressions) are positively correlated with adolescents' physiological responses (heart rate, skin conductance) and subjective emotional responses (pleasure, arousal, dominance) ($p<0.01$), and the correlation coefficients are relatively high (0.35-0.68). It can be seen that more obvious symbolic coding in gender-inclusive representations is associated with stronger and more positive emotions. Stereotypical gender representations also show a relatively small positive correlation with the emotional responses of adolescents ($p < 0.05$), but with a lower coefficient (0.15-0.32); therefore, they have a weaker positive effect on adolescents' emotions.

4.2 Regression Analysis

Multiple linear regression analysis was conducted on the subjective emotional responses (pleasure, arousal, dominance) of adolescents as dependent variables, and gender-represented symbolic characteristics (multivariate and stereotyped) were used as independent variables to examine the predictive effect of symbolic characteristics on emotional responses (see Table 5).

Table 5: Regression Analysis of Gender-Representative Symbolic Features on Adolescent Emotional Reactions (N=286).

dependent variable	argument	regression coefficient(β)	t	p	R²	F
Pleasure(P)	Multiple Symbol Features	0.58	12.34	0.000	0.42	89.76
	Stereotypical Symbol Features	0.15	3.21	0.002		
awaken(A)	Multiple Symbol Features	0.63	13.56	0.000	0.48	105.43
	Stereotypical Symbol Features	0.12	2.89	0.004		
dominance(D)	Multiple Symbol Features	0.55	11.78	0.000	0.39	82.34
	Stereotypical Symbol Features	0.14	3.01	0.003		

As shown in Table 5, all symbolic features of various gender representations have a significant positive predictive effect on adolescents' pleasure, arousal and dominance ($p<0.001$), and these predictors have relatively large regression coefficients (0.55-0.63) and strong explanatory power (R^2=0.39-0.48). Stereotypical gender representation symbols have shown a significant positive predictive effect on adolescents' emotional responses ($p<0.01$), but their coefficients (0.12-0.15) are relatively small, and their explanatory power is weaker. According to the above results, different symbols of gender representation are the main reasons for the positive emotions in teenagers, and stereotypical depictions have a relatively small impact.

4.3 Mediation effect analysis

Based on cognitive appraisal theory and the results of our qualitative in-depth interviews, this study proposed a cognitive mediation model: The symbolic attributes of AI-generated gender representation do not directly cause emotional reactions; rather, they first alter adolescents' higher-order gender cognition, and only then do these cognitive changes lead to changes in emotion.

Bootstrap with 5,000 resamples was employed to test the mediation hypothesis rigorously. In order to determine whether "gender cognition" is a statistically significant mediator of the regression results above, a Sobel test was also performed.

$$Z = \frac{a \times b}{\sqrt{b^2 s_a^2 + a^2 s_b^2}} \tag{3}$$

In this equation, a represents the unstandardized regression coefficient of the multi-modal symbolic features on the mediating variable (gender cognition), and b represents the coefficient of gender cognition on the dependent variable (emotional response). The variables s_a and s_b denote their respective standard errors. A resulting Z-score greater than 1.96 confirms a significant mediation effect at the 0.05 level.

Table 6: Mediation Effect Test Results of Gender Cognition (N=286)

route	regression coefficient(β)	tandard error	t	p	95%CI
Multimodal symbolic features → gender cognition	0.45	0.06	7.50	0.000	[0.33-0.57]
Gender perception → positive emotional response	0.51	0.07	7.29	0.000	[0.37-0.65]
Multimodal symbolic features trigger positive emotional responses (direct effect)	0.37	0.08	4.63	0.000	[0.21-0.53]
Multimodal symbolic features trigger positive emotional responses (overall effect)	0.60	0.07	8.57	0.000	[0.46-0.74]

As shown in Table 6, the analytical results and Sobel test confirm that gender cognition mediates to some extent between the various symbolic attributes of AI images and positive emotions among adolescents. The calculated indirect effect is 0.23 (95% CI: [0.15, 0.31]), which accounts for 38.3 per cent of the total indirect effect.

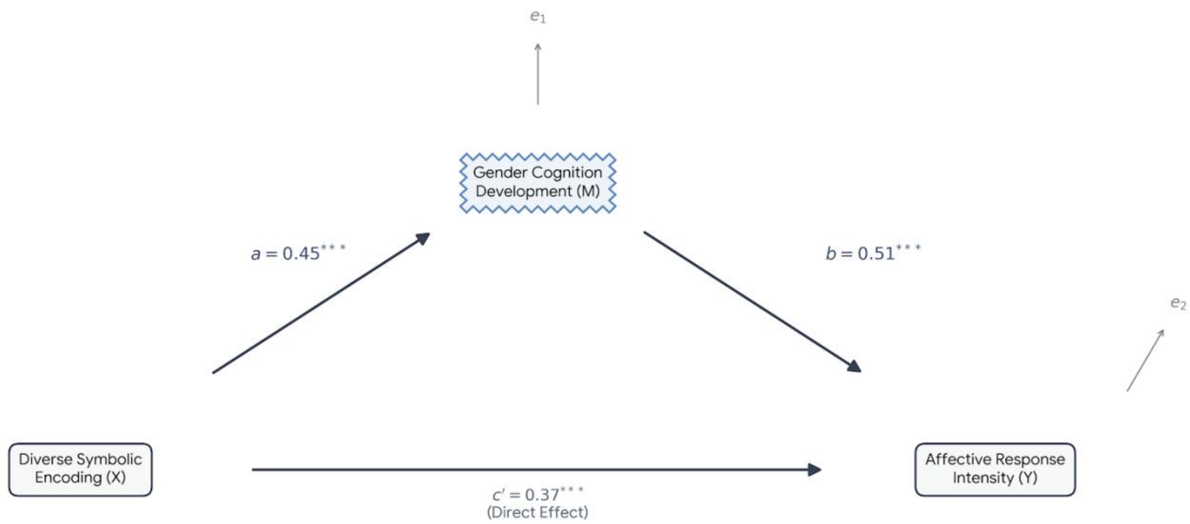

Figure 5: Path Diagram of the Mediation Effect of Gender Cognition in the Multimodal Symbolic Features-Adolescent Emotional Responses Path

However, in the observation of the representative-group-stereotype construction, the mediating effect of gender cognition disappeared and was determined to be statistically insignificant (95% CI: [-0.05, 0.12], crossing zero). Theories are not the same. Therefore, when young people come across various boundary-breaking gender symbols, they are prompted to be more actively engaged with these symbols and rethink their own beliefs about gender equality; as a result, they have profound emotional responses and positive arousal. Conversely, stereotypical symbols are based on automatic, heuristic processing; they do not require deep cognitive reappraisal and thus result in only shallow and limited emotional responses.

5 Summary

Based on a combination of structuralist semiotics and affective computing, this study has used multiple means to explore how gender portrayals in generative artificial intelligence's images shape the emotions of young people: quantitative content analysis; physiological experiment; and in-depth interviews.

First, according to the semiotic content analysis, AI-generated images have a dual-coding system. On the other hand, algorithms are still biased and reproduce outdated gender roles (e.g., hyper-masculine dark aesthetics and passive feminine depictions). At the same time, the new creative flexibility of AI also serves as a catalyst for pluralistic breakthroughs and promotes the normalisation of androgynous, diverse and equitable gender expressions that challenge historical norms.

Second, empirical affective computing data show that adolescents have distinctly polarised emotional responses to these digital representations. Multiple types of gender symbols tend to induce a relatively high level of physiological arousal (such as increased heart rate and skin conductance) and positive subjective emotions (such as pleasure and a sense of control) in people compared with exposure to traditional stereotypes. In addition, this positive emotional response is stronger among young girls and other junior high school students; thus, these groups may be more willing to receive visual narratives that promote gender equality and empowerment.

Thirdly, based on the mechanism analysis of our study, gender cognition serves as the intermediary. Pluralistic AI symbols actively construct and extend the sense of gender equality for adolescents, and this cognitive expansion subsequently mediates and predicts positive emotional arousal. Traditional stereotypes fail to trigger this cognitive path and are therefore having a reduced impact on progressive youth consciousness. In short, according to Barthes' theory of semiotics, although conventional stereotypes of AI-generated images aim to "naturalise" historical gender inequality, multiple different ways of representation have been established that can also be considered new "myths" of gender equality today.

Theoretical and Practical Implications: Theoretically, by combining the deep interpretive quality of semiotics with the objective, measurable data of affective computing, this paper presents a new and highly reproducible research system for evaluating human-computer interaction (HCI) and digital media consumption. In practice, the above results are urgent requirements for the generative AI industry and algorithmic governance organs. Increase the amount of training data and reduce the transmission of outdated gender stereotypes in the AI. At the same time, educators and policymakers can utilise the positive emotions that people experience when viewing various AI images to create new media literacy classes, helping young people learn how to think about, make sense of, and feel about their lives in the age of artificial intelligence.

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