Gender Bias in AI Generated Spatial Atmospheres

Analysing gender-specific distortions in AI-generated spatial atmospheres inspired by the characters in Elias Canetti's „The Earwitness"

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Generative image AI (Artificial Intelligence) is reshaping the design process; however, it often reproduces societal gender biases embedded in its training data. While AI's role in reinforcing gendered stereotypes in human representation is well-documented, its impact on spatial design remains underexplored. Discussions such as Hannah Rozenberg's "Building Without Bias" highlight the urgency to address these biases within architecture and design. Drawing on Elias Canetti's "The Earwitness", a book in which characters are intentionally defined by gendered descriptors, this study uses these representations as a framework to analyze how generative AI translates such terms into visual and spatial outputs. The descriptions of fifty characters were processed through a standardized AI prompt, generating spatial interpretations analyzed via quantitative image processing and Likert-scale classification. Key parameters -luminance, edge sharpness, curvature and color temperature- were measured to assess gender-coded tendencies. The analysis revealed that AI systematically reinforces gendered spatial conventions, with masculine-associated descriptors producing angular, darker environments, while feminine-associated terms yield softer, brighter spaces. Additionally, a significant disparity in the representation of female-coded spaces was observed, as they appeared less frequently. These findings underscore the need for a more ethical and reflective approach to AI development, ensuring that generative tools challenge rather than perpetuate existing societal biases.

Keywords: *Generative Image AI, Gender Bias, Spatial Design, Stereotypes, Atmospheric Spaces.*

INTRODUCTION

Architecture has always been a visually driven discipline, relying on two-dimensional representations to communicate, conceptualize, and shape spatial environments. Since antiquity, images have served as a primary medium for understanding and constructing reality, as Aristotle described the imitation of nature as both an inherent human desire and a method of knowledge production (Meisenheimer, 2018, p. 163). This visual dependency remains central to architectural practice today, particularly in the digital age, where representations increasingly mediate the design process (Fischer and Delitz, 2009, p. 343; Mörtenböck, 2001, p. 165).

With the integration of artificial intelligence (AI), architecture is no longer solely built but also simulated. Donna Haraway (2006, pp. 117–158) describes the dissolution of boundaries between human and machine -a concept that also applies to

architectural design, where computational tools generate spatial atmospheres rather than merely representing them. These AI-driven systems extend architectural conventions but inherit the biases embedded in their training data.

As Philip Ursprung (2013) emphasizes, architecture is not only constructed but also produced and understood through images as part of a broader cultural practice. AI-generated visuals, in this context, are more than neutral depictions -they actively shape how space is perceived and interpreted. The transformation from text to image thus becomes a process of visual encoding, influenced by aesthetic traditions and embedded cultural norms. Haines et al. (2016) show that gender stereotypes remain deeply rooted in society. Since AI systems learn from existing structures and rely on biased datasets, they tend to reinforce rather than challenge prevailing gender norms, thereby further embedding stereotypes into digital architectural imagery.

Although not yet published in a peer-reviewed format, Hannah Rozenberg's research (urbanNext, 2021) offers valuable first insights into how architecture can be used to reveal and counteract gender bias. Through computational analysis, she identifies spatial elements with "zero gender units," demonstrating how architectural interventions may neutralize gendered attributions. Her work underscores the potential to retrain AI-driven design tools toward more inclusive and equitable spatial practices.

Unlike previous studies (Sun et al., 2024; Wu et al., 2023), which primarily focused on gender bias in human representation within generative imagery, this study extends the analysis to architectural atmospheres. Rather than evaluating facial or bodily traits, it applies visual-spatial parameters to test how AI codifies textual gender markers into spatial form. This approach is grounded in the understanding that architecture -traditionally shaped by gendered aesthetics- encodes spatial attributes such as form, materiality, and lighting within binary gender norms (Fischer and Delitz, 2009, p. 265).

Using Elias Canetti's The Earwitness (Canetti, 1979) as a case study, it examines how AI translates textual character descriptions into spatial imagery and whether these interpretations reinforce gendered spatial conventions. Canetti's literary method, which assigns atmospheric qualities to characters, provides a unique framework for investigating how AI-generated environments reflect or challenge gendered perceptions in architecture.

This study does not aim to prove the mere existence of gender bias in generative AI -a fact already widely documented. Instead, it seeks to examine how such biases are translated into spatial representation. By applying a controlled, text-based method to architectural atmospheres, this paper seeks to offer initial insights into how generative AI may encode gender and to highlight possible asymmetries in the depiction of masculine- versus feminine-coded spaces. Gaining a better understanding of these tendencies could contribute to the ongoing discussion about binary structures in digital spatial design.

METHODOLOGY

This study integrates insights from architectural theory, perception research, and AI bias analysis. A four-step methodology was employed, which will be elaborated in the following sections, aiming to systematically identify recurring patterns.

Step 1 Text-to-Image Transformation

The 50 characters described by Canetti were translated into AI-generated spatial representations using DALL·E 3 by OpenAI. To ensure statistical reliability, four image variations per character were generated using an identical prompt, resulting in a total dataset of 200 images.

To maintain consistency and comparability, a standardized prompt was applied across all characters. The full, unmodified English translation of Canetti's original text was used to eliminate subjective reinterpretation.

"Create an atmospheric space that embodies the character traits of [Insert Character Name]. The space should visually translate their defining qualities in terms of form, light, color, and materiality. [Insert complete character text from Canetti]."

This prompt was designed to ensure that the AI independently selects which textual elements to translate into spatial representations, without additional stylistic or emotional framing. Still, it is important to acknowledge the "black box" nature of DALL·E's generative process. Prompt interpretation may be influenced by hidden weightings, stochastic variations, and reinforcement learning from human feedback (RLHF), limiting full control over image outputs. While standardized prompts increase consistency, the influence of individual words remains opaque. DALL·E 3 does not offer interpretability regarding which input terms are prioritized, nor does it allow control over the weighting of gendered, emotional, or material descriptors. As such, the study is limited to analyzing visible outputs while acknowledging the opacity of the generative mechanism.

The explicit inclusion of the parameters -form, light, color, and materiality- was intended to guide the AI toward spatial characteristics, aligning with Gernot Böhme's theoretical framework on architectural atmospheres and the role of these fundamental attributes in shaping spatial perception (Böhme, 2013, p. 16). Similar perspectives are reflected in works such as Fischer and Delitz (2009) and Kuhlmann (2013), who emphasize the social construction of space and its role in reproducing gendered hierarchies.

Step 2 Quantitative Image Analysis

The previously defined parameters -form, light, color, and materiality- were analyzed using automated computational methods in Python with OpenCV. For each parameter, specific hypotheses were formulated based on existing research, aligning with prior findings on gendered spatial perception and atmosphere.

Luminance. The Luminance was evaluated by calculating the average luminance value across each image, applying the ITU BT.601 formula to reflect perceived brightness (Algorithm 1). The mean luminance and standard deviation were recorded to determine variations in brightness.

Algorithm 1: Luminance
b, g, r = cv2.split(image)
Luminance = 0.299 * *r* + 0.587 * *g* + 0.114 * *b*
return *np.mean(Luminance), np.std(Luminance)*

Hypothesis 1. Based on prior research, masculine-coded spaces are expected to be darker, while feminine-coded spaces exhibit higher brightness levels (Gaar, 2019, p. 49).

Edges and angularity. The Edges and angularity were measured using the total number of edge pixels detected via the Canny Edge Detection algorithm (Algorithm 2). Edge density analysis was employed to quantify brightness transitions, serving as an indicator of spatial angularity.

Algorithm 2: Edges
gray =
cv2.cvtColor(image,cv2.COLOR_BGR2GRAY*)*
edges = cv2.Canny(gray, 100, 200)
edges_quantity = np.sum(edges > 0)
return *edges_quantity*

Hypothesis 2. Masculine-coded spaces are hypothesized to exhibit more edges, while feminine-coded spaces are expected to have less edges (Lieven et al., 2015; Stroessner et al., 2020, p. 149; Fischer and Delitz, 2009, p. 265).

Curvature. The Curvature was assessed through Sobel gradient calculations (Algorithm 3), determining the rate of intensity changes along the x- and y-axes. Gradient angles of detected edges

were analyzed to quantify the proportion of curvatures within each image.

Algorithm 3: Curvature
```
image = cv2.imread(image_path,
cv2.IMREAD_GRAYSCALE)
edges = cv2.Canny(image, 100, 200)
sobelx = cv2.Sobel(edges, cv2.CV_64F, 1, 0,ksize=5)
sobely = cv2.Sobel(edges, cv2.CV_64F, 0, 1,ksize=5)
angles = np.arctan2(sobely, sobelx)
curvature_hist = np.histogram(angles, bins=30,
range = (-np.pi, np.pi))[0]
high_curvature_score = np.sum(curvature_hist
[10:20]) / np.sum(curvature_hist)
return high_curvature_score
```

Hypothesis 3. Feminine-coded spaces are expected to exhibit greater curvature than masculine-coded spaces. (Lieven et al., 2015; Stroessner et al., 2020, p. 149; Fischer and Delitz, 2009, p. 265).

Color. The Color was analyzed by measuring composition in terms of RGB values, LAB values, hue, and saturation within the HSV color space. The most suitable metric for evaluation was color temperature in Kelvin (Algorithm 4)., as it effectively quantifies the balance between blue (cool) and red (warm) tones, thereby assessing temperature shifts across the images.

Algorithm 4: Color Temperature
```
image = cv2.imread(image_path)
avg_color = np.mean(image, axis=(0, 1))
r, g, b = avg_color[::-1]
temp_k = 1000 + ((b - r) / (b + r + 1e-5)) * 4000
return temp_k
```

Hypothesis 4. It is hypothesized that masculine-coded spaces are represented with cooler color temperatures, whereas feminine-coded spaces appear warmer (Wigley and Dornelles, 2021, p. 367).

Step 3 Statistical Analysis

The final dataset was analyzed. Descriptive statistics were employed to calculate mean values and standard deviations for each visual parameter, while absolute values were normalized to relative scores ranging from 0 to 100, for better comparability.

Inferential testing was conducted using t-tests to determine statistically significant differences, with an alpha level of 0.05.

To visualize trends and distributions across gender-coded parameters, histograms were generated, providing a comprehensive representation of data patterns.

Step 4 Likert Scale Classification

Visual attributes were classified using a Likert scale ranging from 1 (masculine-coded) to 5 (feminine-coded), based on established gender associations in prior research. This classification provided a structured framework for evaluating whether AI-generated architectural atmospheres aligned with stereotypical gendered spatial representations.

The scoring procedure involved calculating the mean values across the four generated images per character. Each character was evaluated based on luminance, edge sharpness, curvature, and color temperature, with scores assigned according to the Likert scale. The overall spatial representation for each character was then determined by summing the individual scores of all spatial attributes and placing it along a gender spectrum. Final Likert scores were categorized as follows:

- 1 (4–7 points) masculine-coded
- 2 (8–11 points) rather masculine-coded
- 3 (12 points) neutral classification
- 4 (13–16 points) rather feminine-coded
- 5 (17–20 points) feminine-coded

Characters whose cumulative scores resulted in a neutral classification (Likert 3) were not excluded from the dataset but were also not used to draw concrete conclusions regarding gender bias, as their visual characteristics could not be clearly attributed

to either end of the gender spectrum. Instead, the analysis focused on distinct patterns found in characters with clearly gender-coded scores (1–2 or 4–5). The presence of neutral cases underscores the complexity of spatial interpretation and the AI's inconsistent handling of non-binary descriptors.

Furthermore, the percentage of characters classified as masculine- or feminine-coded was compared to the actual gender descriptions in the original text, allowing for an evaluation of AI-driven gender distortions in spatial representation.

Case Study Gender-Atypical Characters

Beyond general trends, specific characters with gender-atypical descriptions were examined to assess how AI evaluates conflicting gender markers. Three characters were selected based on their atypical descriptions.

The Tear Warmer, a male character with traits traditionally associated with femininity, was analyzed to determine whether AI-generated spaces align with his emotional characteristics or adhere to masculine-coded spatial norms.

Additionally, the **Beauty-Newt** was included in this case study, as he is described as obsessed with beauty -an attribute traditionally associated with femininity (Böhme, 2013, p. 20).

Conversely, the **Granite Cultivator**, a female character characterized by traditionally masculine attributes, was examined to assess whether her AI-generated space reflects her described traits or conforms to conventional femininity.

This selection allows for an analysis of how AI spatially represents gendered aesthetic concepts, particularly in relation to characters whose descriptions challenge conventional gender norms.

RESULTS

The analysis of AI-generated architectural representations was conducted using quantitative image processing techniques and qualitative assessments, as described in Step 2. The results are presented below according to key visual parameters: luminance, edge sharpness, curvature, color analysis, and materiality.

Luminance

Female-coded spaces exhibit higher mean luminance ($M = 44.20$) than male-coded spaces ($M = 35.80$), as shown in Figure 1. This statistically significant difference ($p \approx 0.0025$) supports Hypothesis 1, linking femininity to increased brightness and open, illuminated spatial qualities.

Edge Sharpness

Male-coded spaces display higher edge sharpness ($M = 56.97$) compared to female-coded spaces ($M = 42.08$), as illustrated in Figure 2. The statistically significant difference ($p < 0.001$) confirms Hypothesis 2, associating masculinity with stronger contours and angular architectural forms.

Curvature

Female-coded spaces have a higher mean curvature ($M = 52.81$) than male-coded spaces ($M = 36.88$), as shown in Figure 3. The significant difference ($p < 0.001$) supports Hypothesis H3, indicating a preference for softer, rounded shapes in feminine representations.

Color Analysis

No statistically significant differences were found in color distribution (male: $M = 54.01$, female: $M = 50.74$, $p \approx 0.34$), as shown in Figure 4. This contradicts Hypothesis 4 regarding color differentiation, indicating no systematic gender-based color coding by the AI.

Gender Attribution

The classification of images was based on a Likert-scale evaluation as described in Step 4.

- Male Characters Represented with Male-Typical Spaces: 79.3% (23 of 29)
- Female Characters Represented with Female-Typical Spaces: 52.4% (11 of 21)

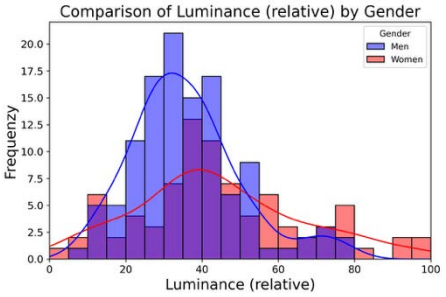

Figure 1
Histogram shows the Comparison of Luminance by Gender

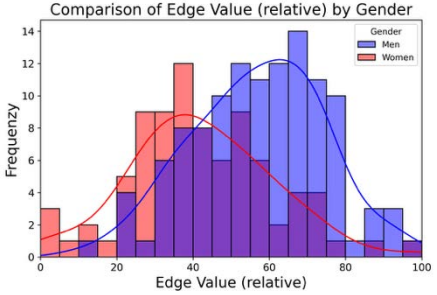

Figure 2
Histogram shows the Comparison of Edge Values by Gender

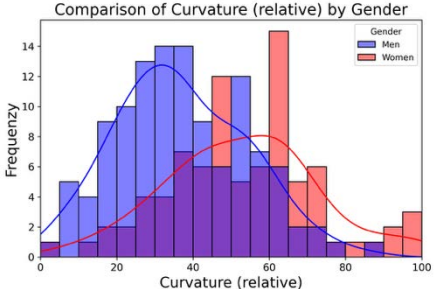

Figure 3
Histogram shows the Comparison of Curvature by Gender

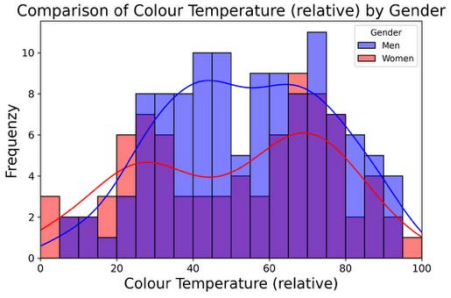

Figure 4
Histogram shows the Comparison of Color Temperature by Gender

These results indicate that male characters are more consistently represented in spaces aligned with their gender coding, whereas female representations often appearing either fully feminine or strongly masculine. This suggests that the AI responds differently depending on the character group.

Case Study

The AI-generated representation of the **Tear-Warmer** (Figure 5) exhibits a dark atmosphere with some curvature and soft textures. The classification resulted in a score of 2, indicating a tendency toward a masculine interpretation. The original character is male, which aligns with the AI's output. However, the text describes the character in highly emotional and melancholic terms, typically associated with femininity. It therefore remains unclear whether the darkness in the spatial output results primarily from the emotional tone of the description or from the character's gender attribution. This ambiguity illustrates the challenge of distinguishing emotional influence from gender coding in AI-generated architectural atmospheres.

In the case of the **Granite-Cultivator** (Figure 6), the generated space is characterized by a dark atmosphere, strong edges, and harsh transitions. The AI appears to have emphasized angularity and heaviness, creating a highly structured and almost brutal environment. With a classification score of 2, the image is again interpreted as rather masculine - despite the fact that the original character is female. A possible explanation lies in the term *"Granite"*, which is inherently associated with hardness and weight. These attributes may have led the AI to assign design traits typically linked to masculinity, such as sharp edges and rigid forms.

By contrast, the **Beauty-Newt** (Figure 7) is depicted in an opulent setting dominated by golden hues and warm lighting, resulting in a highly decorative aesthetic. The classification yielded a score of 4, suggesting a rather feminine coding - although the character is actually male. The AI's association of gold, warmth, and opulence with femininity may stem from the term *"Beauty"*, which

Figure 5
AI-generated image of The Tear-warmer

Figure 6
AI-generated image of The Granite-Cultivator

Figure 7
AI-generated image of The Beauty-Newt

has historically been linked to feminine connotations (Gaar, 2019, p. 48, pp. 57).

The case study was intended to provide insight into which aspects the AI prioritizes based on textual descriptions. However, this question cannot be fully resolved due to inconsistencies in interpretation. For instance, all three case study characters received a neutral score of 3 for the attributes curvature and edge, making it difficult to draw clear conclusions. These parameters are therefore not further discussed in this context.

By contrast, luminance and color offered more meaningful insights, as they showed clearer variation across the case studies and appeared more relevant. However, these parameters may also reflect emotional content. This became particularly evident in the case of the Tear-Warmer. Since sadness is often associated with femininity, a brighter atmosphere might have been expected. As this was not the case, it is possible that the AI prioritized emotional tone over gendered descriptors in this instance. This ambiguity makes it difficult to determine whether luminance and color reflect gender or emotional aspects and thus limits the conclusiveness of the results.

Additionally, the results suggest that material and metaphorical terms such as “granite,” “tear,” or “beauty” carry significant weight for the AI, often overriding emotional or gendered cues in the spatial output.

CONCLUSION

The results indicate a strong tendency for AI-generated spaces to align with traditional gendered spatial perceptions. Male-coded characters are predominantly associated with angular, darker environments, whereas female-coded characters are placed in brighter, more curved spaces. Hypotheses 1–3 were confirmed, reinforcing the link between gendered spatial attributes and AI-generated representations. However, contrary to expectations, Hypothesis 4 could not be validated. While previous research identified color as a strong gender indicator (Wigley and Dornelles, 2021, p. 367), no significant

differentiation was observed in this study, making the interpretation of results more complex.

A notable finding is the asymmetry in gender representation. **Masculine-coded spaces** appear in **79.3%** of male cases, whereas distinctly **feminine-coded environments** account for only **52.4%** of the female characters. This imbalance reflects patterns, which were already found in human AI representation (Sun et al., 2024; Wu et al., 2023), where masculinity often serves as the default. Furthermore, female characters were either depicted with highly stereotypical femininity or overridden by masculine spatial traits, reducing the overall presence of distinctly feminine-coded environments. Cases such as **The Narrow-smeller** (Figure 8) and **The Allusive Woman** (Figure 9) demonstrate exaggerated femininity (Likert Scale 5), in contrast to the neutralization of masculinity, reinforcing concerns that women are either hyper-feminized or absorbed into male-coded aesthetics when they exhibit non-stereotypical traits.

Male characters, by contrast, are rarely feminized. **The Tear-Warmer**, for instance, retains a dark and structurally complex spatial quality despite being described as emotional -an attribute more commonly associated with femininity. In contrast, female characters with masculine traits, such as **The Granite-Cultivator**, are often visually overridden by traditionally masculine design elements. This raises concern that strength in female characters is translated into masculinity rather than being represented as a neutral or independent trait.

These findings not only confirm the presence of gender bias but also expand the current discourse by shifting the focus from human representation to the atmospheric coding of space. The study shows how gendered assumptions are embedded in spatial qualities like luminance, curvature, and materiality, offering a new perspective to the understanding of bias in generative systems -one that connects computational processes with architectural perception and opens critical questions for spatial design.

Figure 8
AI-generated image of The Narrow-Smeller

Figure 9
AI-generated image of The Allusive Woman

OUTLOOK

Even though the results clearly indicate an asymmetry in the representation of masculine- and feminine-coded spaces (Table 1, 2), these findings should be viewed from multiple perspectives. It remains uncertain whether the AI primarily responds to the character's gender, emotional tone, or the spatial descriptors used in the text. The generative model appears unable to fully grasp the complexity of the characters, often amplifying specific aspects while overlooking others.

AI-generated images risk perpetuating societal power structures by unconsciously reinforcing patriarchal visual codes. These biases manifest

through subtle yet pervasive design choices that sustain traditional gendered aesthetics (Kuhlmann, 2013). To counteract this, a gender-neutral approach must go beyond superficial adjustments and instead challenge the underlying logic of gendered visual representation.

As Iris Bohnet (2016, p. 285) emphasizes, design itself can act as a tool for reducing bias. For designers, this means critically reflecting on the language used in prompts and iterating toward more balanced spatial representations. Replacing gendered adjectives with spatially neutral descriptors, refining prompt precision, and advocating for tools that offer adjustable bias filters are important steps toward a more gender-equal approach in generative workflows. For instance, using explicit spatial terms like “a room with sharp edges and cold lighting” instead of abstract descriptors like “dominant” may help minimize stereotypical associations and reveal new pathways for inclusive AI design.

To apply these insights in practice, design education could include prompt analysis, encouraging students to explore inclusive vocabulary and assess the resulting atmospheres. In professional settings, AI-generated visuals could be paired with bias audits, simple checklists or visual mapping tools that flag stereotypical elements. For developers, this opens the opportunity to build customizable prompting environments with integrated bias indicators or training filters, allowing for more inclusive outputs.

Gender-neutral design is not merely a trend but a reflection of a broader commitment to recognizing diverse gender identities and expressions. It reminds us that design is not confined to binary frameworks but is a creative discipline that honors the complexity of human experience. A truly gender-neutral or gender-dynamic AI would therefore need to go beyond the reproduction of existing stereotypes and actively develop new, equitable visual coding strategies.

To support this shift, further analytical tools are needed to examine how gendered patterns emerge in generative processes. A correlation matrix between linguistic input -particularly descriptors linked to emotion or metaphor- and visual parameters could provide deeper insights into how such attributions are encoded. While this could not be realized within the scope of this paper, it represents a crucial direction for future investigation. Thus, the question remains how AI can be designed not just to reinforce patterns but to create more diverse and inclusive visual worlds.

Table 1
Likert Scale evaluation male Characters

MALE

CHARACTER NAME	Edge Value	Curvature	Luminance	Color / Temperature	**Total**	**Range**
THE BEAUTY-NEWT	3	3	3	4	13	4
THE BEQUEATHED MAN	4	3	2	3	12	3
THE BLIND MAN	2	1	2	3	8	2
THE CORPSE-SKULKER	4	3	2	3	12	3
THE DAMAGE-FRESH MAN	2	2	2	3	9	2
THE DELAYER	3	3	3	3	12	3
THE EARLY WORDER	2	2	4	1	9	2
THE FARWITNESS	4	4	2	2	12	3
THE FAME-TESTER	2	2	2	3	9	2
THE FUN-RUNNER	2	2	3	2	9	2
THE GOD-SWANKER	2	2	3	4	11	2
THE HERO-TUGGER	4	3	2	2	11	2
THE HOME-BITER	2	2	2	4	10	2
THE HUMILITY-FOREBEAR	4	3	2	2	11	2
THE LONG-CHANGER	2	2	2	5	11	2
THE LOSER	2	2	3	3	10	2
THE MAESTROSO	3	3	3	4	13	4
THE MAN-MAD MAN	3	3	2	3	11	2
THE MISSPEAKER	2	2	2	2	8	2
THE NAME-LICKER	2	2	3	3	10	2
THE NEVER-MUST	3	3	3	2	11	2
THE PAPER DRUNKARD	2	2	2	4	10	2
THE STATURE-EXPLORER	2	2	2	4	10	2
THE SUBMITTER	2	2	4	2	10	2
THE TATTLETALE	2	2	1	3	8	2
THE TEAR-WARMER	3	3	1	2	9	2
THE WATER-HARBORER	2	2	2	1	7	1
THE WILE-CATCHER	3	2	2	2	9	2
THE WOE-ADMINISTRATOR	3	2	2	2	9	2
				Total same 3	**4**	
				Total above 3	**2**	
				Total under 3	**23**	
				Numbers of characters	**29**	

Table 2
Likert Scale evaluation female Characters

FEMALE

CHARACTER NAME	Edge Value	Curvature	Luminance	Color / Temperature	**Total**	**Range**
THE ALLUSIVE WOMAN	5	5	4	3	17	5
THE ARCHEOCRAT	3	2	2	4	11	2
THE BITTER-TANGLER	2	2	2	2	8	2
THE CULPRIT	3	3	2	2	10	2
THE DEFECTIVE	3	3	3	2	11	2
THE GOODS-AND-CHATTELS	3	3	2	5	13	4
THE GRANITE-CULTIVATOR	3	3	3	2	11	2
THE HORSE-DARK WOMAN	4	4	1	4	13	4
THE INVENTED WOMAN	4	4	3	4	15	4
THE KING-PROCLAIMER	2	2	2	4	10	2
THE MAN-SPLENDID WOMAN	4	4	3	4	15	4
THE MOON COUSIN	3	2	3	2	10	2
THE NARROW-SMELLER	5	5	5	2	17	5
THE SELF-GIVER	4	3	2	4	13	4
THE STARRY WOMAN	3	3	2	1	9	2
THE SULTAN-ADDICT	3	3	1	5	12	3
THE SYLLABLE-PURE WOMAN	3	3	4	3	13	4
THE TABLECLOTH-LUNATIC	4	3	5	2	14	4
THE TEMPTED WOMAN	4	4	2	3	13	4
THE THROWN WOMAN	4	4	3	3	14	4
THE TIRED WOMAN	3	2	2	4	11	2
				Total same 3	**1**	
				Total above 3	**11**	
				Total under 3	**9**	
				Numbers of characters	**21**	

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