Study of Aesthetic Curve Design Method Using Impression Word-based Dialogue AI and GAN

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Abstract. This research presents a novel approach for designing free-form curves that serve as foundational elements for free-form surfaces, based on sensitivity. Utilizing “Kansei” words, terms that capture human emotional responses to design, we employ the visual language framework proposed by Harada et al. For the shape design, we utilize fine-tuned clothoid (FTC) curves due to their aesthetic properties. Our methodology involves training a generative adversarial network (GAN) to learn the relationship between visual language and geometric shapes, followed by training a large language model (LLM) to understand the connection between characteristic shapes and Kansei descriptors. The resulting system enables GANs to predict curve shapes from Kansei word descriptions provided by designers through dialogue with an LLM. This paper reports the system development methodology and presents evaluation results obtained from user experiments.

Keywords: Curve design, Aesthetic design, GAN, LLM, Clothoid curve.
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1 INTRODUCTION

The aesthetic design of automobile bodies and home appliances requires careful consideration of visual appeal, with shapes evaluated through curvature analysis, reflection of the scenery, and highlight line assessment [1,8]. Sone and Chiyokura developed an aesthetic surface design method using fourth-order blended NURBS boundary Gregory patches with highlight curves serving as evaluation indices [18]. Similarly, Higashi et al. proposed a surface design method based on locus modification according to highlight line criteria through evolute surface definition [9].

Recent mathematical advances in fine-tuned clothoid (FTC) research have gained significant momentum [15]. The CREST-ED3GE: Evolving Design and Discrete Differential Geometry project [2] focuses on "the geometry of discrete surfaces with developable surfaces as geometric elements and their discrete variational principles," developing both of aesthetic shape theory and innovative design software platforms.

The clothoid curve, recognized as one of the most aesthetically pleasing curves, exhibits curvature that is proportional or inversely proportional to the curve length. Considering the logarithmic distribution of curvature, the generalized formula becomes the FTC curve [15,16]. Therefore, to establish design guidelines for aesthetic shapes, Kobayashi et al. developed an aesthetic design support method using "Kansei" as a keyword and successfully applied it to product development [11]. Harada investigated the relationship between logarithmic curvature distribution and the visual language used to express design concepts, examining the relationship between human sensibility and shape in design applications [6,7].

Recent developments in optimization and artificial intelligence have accelerated research into automatic and interactive shape design systems. Genetic algorithms (GA) represent one promising approach [10]. Cohen investigated shape optimization methods using NURBS curves and GA optimization, focusing on material boundary parametrization and boundary optimization to define specific shapes [3]. Neural networks combined with GA have been employed to explore optimal aesthetic designs. Kobayashi et al. defined optimal design parameters that minimize variance across customers' utilities, explored through multi-objective GA to design products with reduced sensitivity to customer Kansei variation [13].

Generative Adversarial Networks (GANs) [5] comprise generator and discriminator components, where the discriminator evaluates the authenticity of the data generated by the generator and optimizes the design process. This methodology enables new image generation, with MIT successfully applying GANs to aircraft design [17]. Su et al. utilized StyleGAN3 and stable diffusion models to generate creative hair dryer images and enhance image quality [19]. There is also research on convolutional neural networks. Zhang et al. employed a particle swarm optimization convolutional neural network (PSO-CNN) for 3D reconstruction and rendering [21]. Gai et al. used a graph convolutional neural network models to develop creative advertising design systems that accurately capture user interests and behavioral patterns [4]. Much neural network research has focused on image generation applications.

Research similar to this study includes Kobayashi et al.'s aesthetic design synthesis method [12], which uses the semantic differential method to evaluate existing products, extracting decision rules describing relationships between user preferences, impressions, and aesthetic elements using rough set theory. This approach groups customers based on extracted rule similarity and combines decision rules for each group. However, creating designs accommodating diverse customer decision rules remains challenging.

This study aims to design curves, which are the foundation of aesthetic shapes, based on sensibility by training GANs to learn relationships between Harada's visual language and shapes expressed through FTC curves. We subsequently trained LLMs to understand relationships between characteristic shapes and natural language, developing a system where GANs predict curve shapes from language sentences proposed by designers through an LLM dialogue (ChatGPT). This paper reports the system configuration, learning methodology, and user experiment evaluation results.

2 DESIGN SYSTEM DEVELOPMENT

This research develops a system that utilizes the designer's vocabulary to efficiently design cross-sectional curved surface shapes, which primarily determine shape characteristics in 3D curved surface design. The system configuration is shown in Figure 1. The GAN undergoes pretraining on the relationship between vocabulary and shapes for each design shape classification. Users input design intent through the LLM, and the GAN utilizes pretrained data to create appropriate curve shapes and presents them to users. The learning system was developed using Pytorch-StudioGAN (https://github.com/POSTECH-CVLab/PyTorch-StudioGAN) on a Linux (Ubuntu server) with PyCharm Community Edition 2021.2.3 as the development environment. For curve design, we created approximately 60 examples demonstrating relationships between classification and shape representation as textual data. These texts underwent pretraining into GPT-4o-mini using OpenAI Playground's JSONL format. During design dialogue, users input design shapes in natural language through the WebGL interface, and GPT-4o selects the curve generation classification and generates curves using GAN from that selection. We are currently developing functionality for further curve refinement. These processes were implemented using a Unity-developed WebGL interface, with curve generation requests and the results generated by the GAN displayed through the WebSocket interface.

The relationship between design vocabulary and shapes was systematically defined. Table 1 presents curves with typical characteristics and representative vocabulary. Harada proposed five visual languages [6]:

1) Diverging: sharp, energetic
2) Slow: stable, static
3) Converging: Lines are gathered and centripetal
4) Mountain: An impression of diverging curves converged from a boundary
5) Valley: An impression of converging curves diverging from the boundary

Based on these classifications, four initial shape characteristics were selected:

- "Calm": Gives a calm, flat impression.
- "Powerful": Expresses a powerful impression of rounded yet greatly curved forms.
- "Round": Indicates smoothly curved shapes with minimal variation.
- "Sharp": Expresses a shape with prominent flat sections and sharply emphasized endpoints.

Additional vocabulary, including "Medium," "Minimal," "Bulge," "Rapid," and "Momentum," was incorporated to further subdivide curve shape characteristics and increase specificity. This resulted in 8 categories, each containing collections of similar curves. Table 2 lists the parameters for each category. Figure 2 shows the shape of the curves corresponding to classified features. These curves were generated using the FTC curve (logarithmic spiral) expressed as [14,15]:

$$FTC(t, C_0, C_1, C_2, \alpha) = \frac{C_0}{2(C_1+i\alpha)} e^{iC_2} e^{(C_2+i\alpha)t^2} \tag{1}$$

where α represents the curvature-related constant, C0, C1, and C2 are shape-related constants, and t represents the curve parameter. This equation was formulated by Prof. Miura. C0 controls curve amplitude; larger C0 values increase curve amplitude, adjusting the overall scale. C1 controls curve shape, with values changing curvature from smooth to steep, while positive and negative values alter curve shape in different directions. C2 controls the curve phase, determining shift direction, with positive and negative values shifting curves in different directions. α controls curvature degree; larger α values create sharper curvature. Curve shapes can be customized by adjusting these parameters.

Figure 3 shows curve shapes for 40–50 examples (parameters varied within 15% from Table 2) trained with ReACGAN (Rebooting ACGAN: Auxiliary Classifier GANs) using classification and feature vocabulary. The training utilized four GPUs (RTX-A4500) with Tensor Parallelism algorithms for multi-GPU training. Mixed Precision Training algorithms improved large-scale learning and computational speed. The relationship between the generator loss, discriminator loss, and learning steps is shown in Figure 4. The figure demonstrates low loss after approximately 2,000 iterations and stability after 20,000 iterations.

3 EVALUATION OF THE DESIGN SYSTEM

The developed system was evaluated by 15 participants from Tokyo Polytechnic University, including three from the Faculty of Arts and 12 from the Faculty of Engineering. The questionnaire was divided into three categories: "Evaluation of the suitability of the curve and achievement of purpose," "Evaluation of the shape and naturalness of the curve," and "Evaluation of the beauty and impression of the curve," and was rated on a five-point scale.

Figure 5 presents survey results for "Evaluation of the suitability of curves and achievement of purpose," divided into three categories: "As intended," "Appropriate for vocabulary," and "Highly practical." Regarding design intent, many participants responded "Probably so," suggesting that while users were generally satisfied, some were unfamiliar with evaluating curves based on detailed characteristics.

Figure 6 shows survey results for "Evaluation of the shape and naturalness of the curve," divided into four categories: "Feels natural curve," "Feels strongly rounded," "Feels smooth," and "Feels complicated." Ratings were generally high, though the "complexity" category scored lower, likely due to the monotonic nature of the trained curves, resulting in generated curve designs lacking complexity.

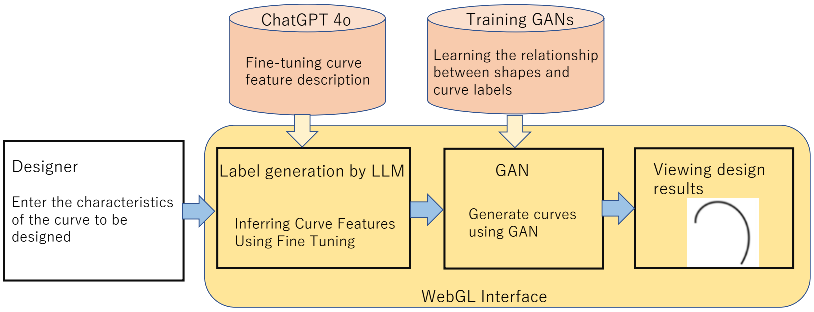


Figure 1: The system configuration of the curve design system.

Type.	Curve Classification	Curve Characteristics word
1	Stable curve, shaped for high speed, Fast speed and stretchy shape, Fast speed, little change, and gentle shape	stable, massive, speedy, run through, high speed, stretchy,
2	The overall curvature is small with little change in shape. Shape with small curvature, small change, and high speed, A shape with low overall curvature and little change at a constant and fast speed	small deviation, small curvature, speedy, high speed
3	Curves that evoke the image of vastness, Fast speed and small shape change, Fast speed, little speed change, and stretchy shape	flat image, large image, small curvature deviation, small curvature,
4	Curves that evoke the image of vastness, Fast speed and small shape change, Fast speed, little speed change, and stretchy shape	vast expanse, Widen, High speed, small curvature deviation, small speed deviation,
5	Shaped for high speed, Fast speed with little change and flat shape, Faster speed and less rounded shape	High speed, run through, small speed deviation, flat, Less rounded
6	Curves that evoke elegance, Dynamic curves	Grace, Elegant image, Dynamic, uplifting,

7	The curve has a large overall curvature, and is reminiscent of a shape that gradually increases in speed from the tip, A curve that represents a shape that accelerates at a constant rate from a point of large curvature, Curves that evoke a rounded and dynamic shape	Large curvature, Gradually increasing speed, Accelerate at a constant velocity rate, large curvature at start area, rounded, dynamic
8	Curves that evoke an organic image, Curves with a powerful image, Curves that imagine a curve with a large to medium curvature,	Organic image, powerful, Bull image, middle is flat, stable, gradual incline,

Table 1: Classification of typical curve shapes and the characteristic vocabulary.

Type	Type of curves and keyword	C0	C1	C2	α
1	calm_medium	1	1	0.39	-1.98
2	calm_minimal	1	1	1	-1.25
3	powerful_bulge	1	2.52	2.62	-4.32
4	powerful_momentum	1	5.14	4.19	-5.74
5	round_medium_rate	1	1	1.64	-3.87
6	round_minimal	1	1	1.11	-2.55
7	sharp_bulge	1	3.81	1.57	-2.91
8	sharp_rapid	1	5.51	1.57	-2.75

Table 2: Type of curves and FTC parameters.

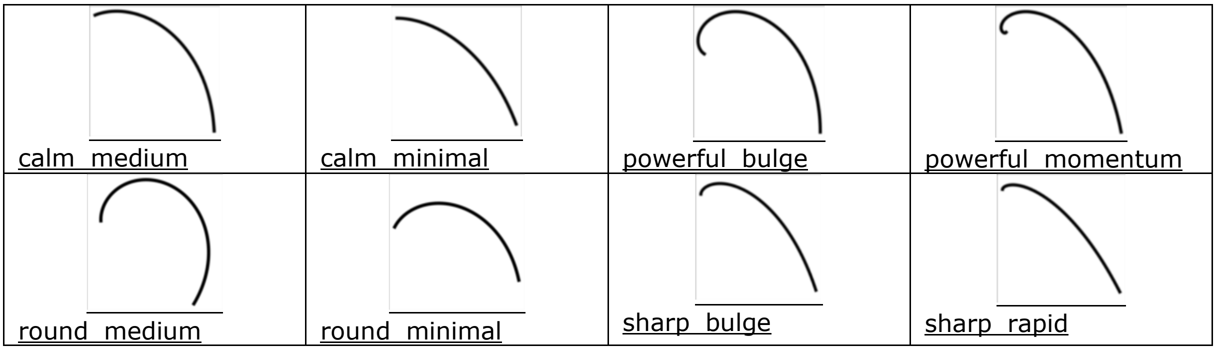
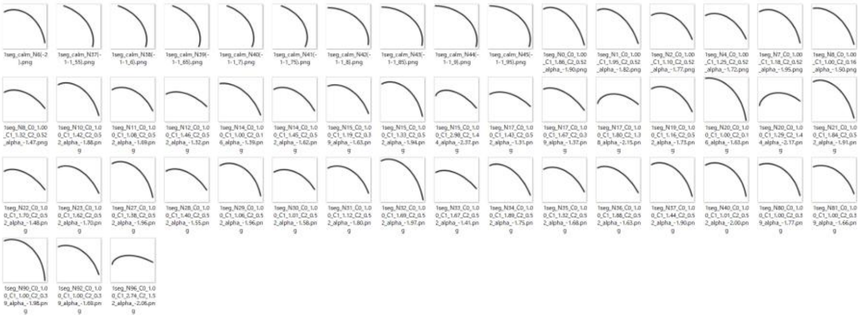
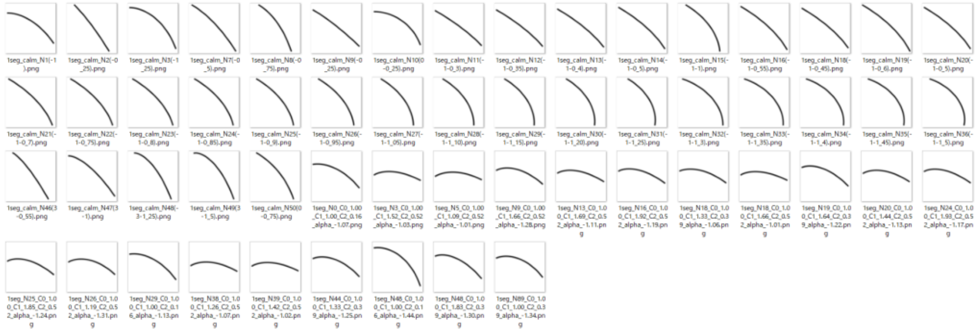


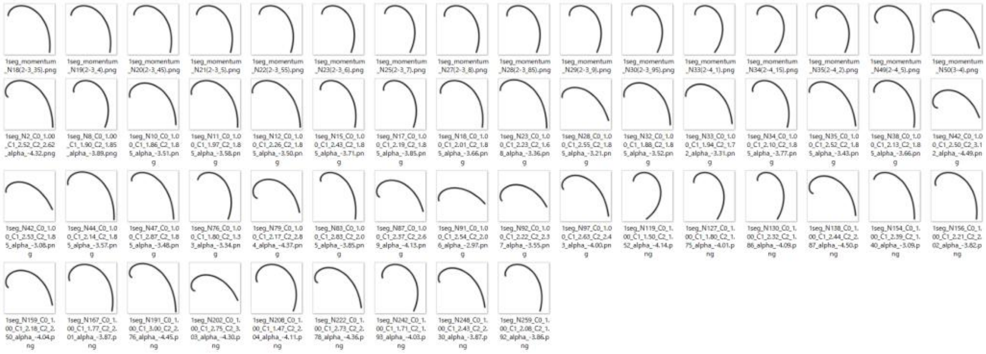
Figure 2: Shape of characteristic curve and classification.



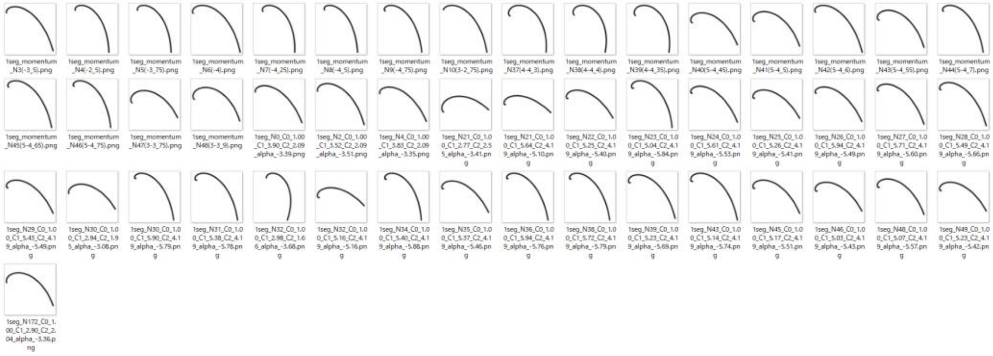
(1) calm_medium shapes.



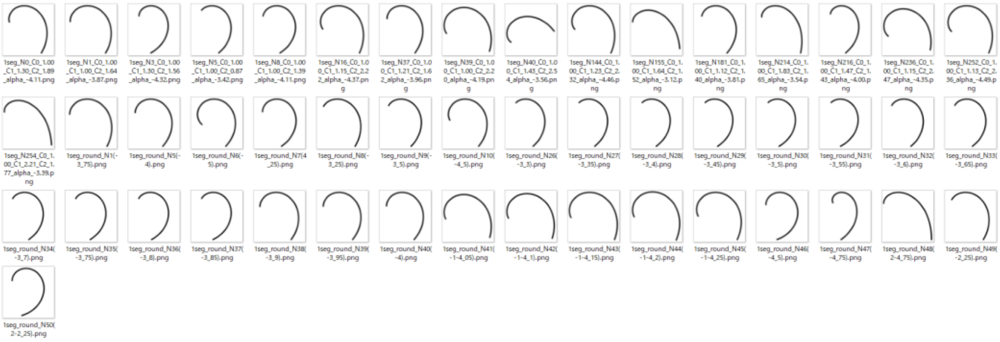
(2) calm_minimal shapes.



(3) powerful_bulge shapes.

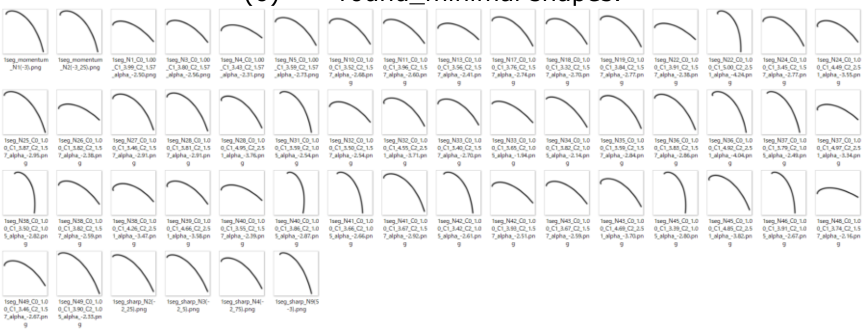


(4) powerful_momentum shapes.

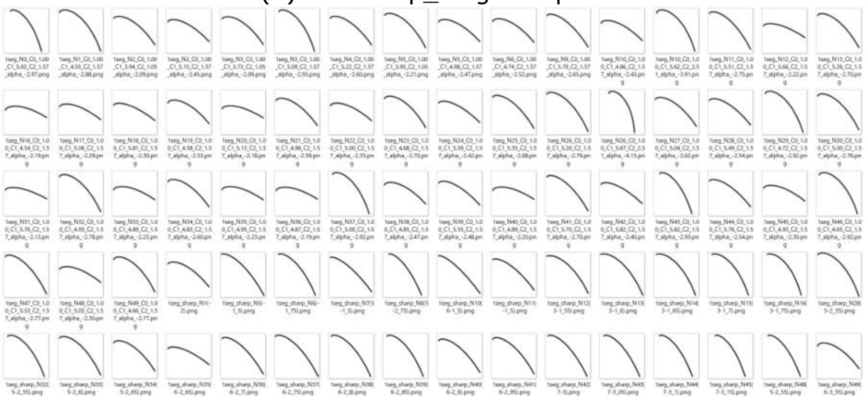


(5) round_medium shapes.

(6) round_minimal shapes.

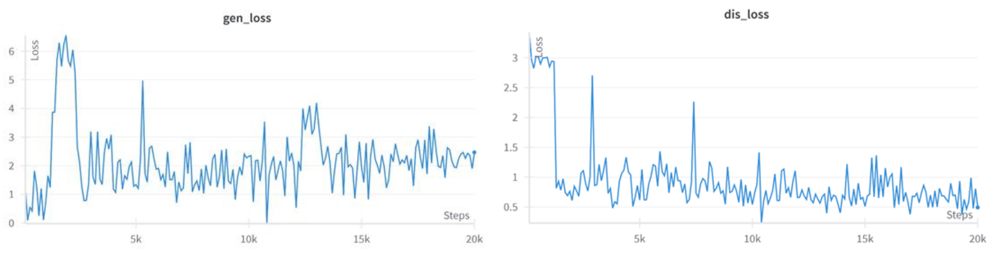


(7) sharp_bulge shapes.



(8) sharp_rapid shapes.

Figure 3: The shape of the curves for 40-50 examples trained with ReACGAN for one classification.



A) Genereator loss B) Discriminator loss

Figure 4: Relationship between the Generator loss, the Discriminator loss, and the learning steps.

Figure 7 shows survey results for "evaluation of the beauty and impression of curved shapes," divided into four categories: "Beautiful," "Attractive," "Harmonious," "Shape is preferred," and "Surprising." Most impressions were positive, though some participants expressed lower ratings for the "attractive" and "Surprising" categories. This indicates a potential desire for more complex or varied designs.

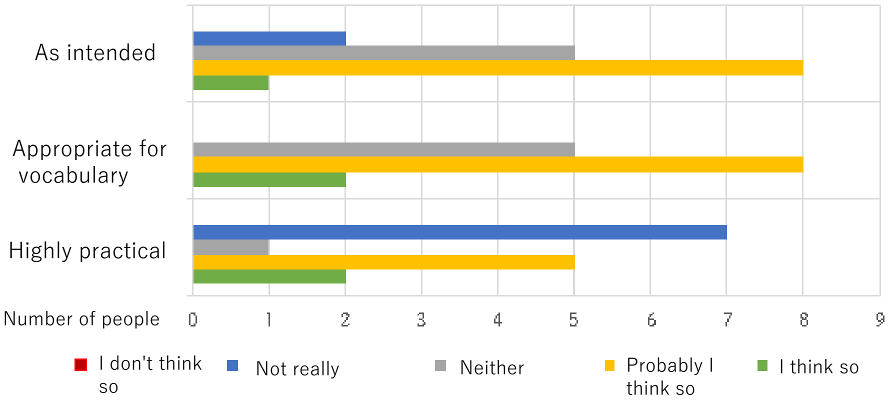


Figure 5: System evaluation results 1.

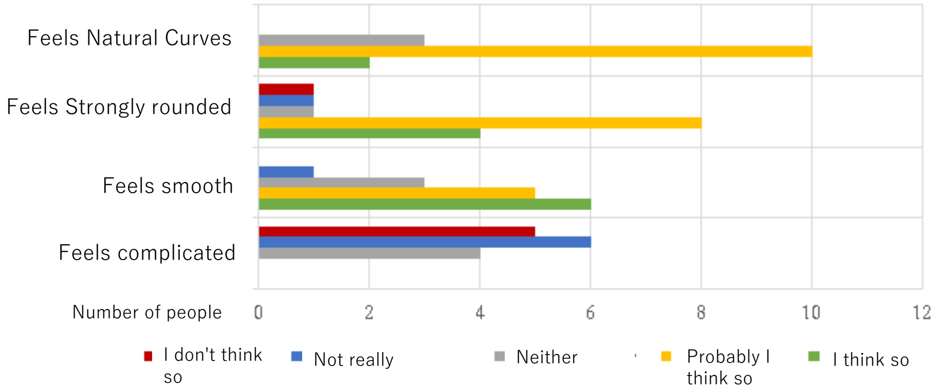


Figure 6: System evaluation results 2.

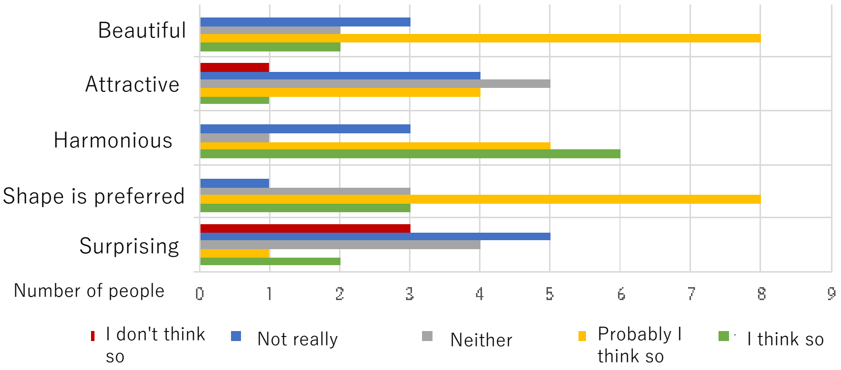


Figure 7: System evaluation results 3.

4 CONCLUSIONS

This study aimed to design cross-sectional curves, fundamental to 3D free-form surface shapes, based on aesthetic sensitivity. By extending Harada's visual aesthetic language and leveraging GANs trained on FTC curves and Kansei vocabulary, we enable designers to express desired features in natural language, with the system generating corresponding curve shapes through LLM–GAN interaction. Initial results demonstrate the system's capability to generate curve shapes that align with user intentions, representing a foundational step toward generating aesthetically appropriate curve shapes. Future work will focus on refining the algorithm to generate curves that more closely match specific design goals, particularly addressing the generation of more complex forms to enhance user satisfaction with surprising and attractive design outcomes.

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EXPERIMENT

This study was approved by the ethics committee of Tokyo Polytechnic University (No.2024-12).

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