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DECISION MAKING IN PROCESS OF BOARD GAMES ARTWORK DESIGN USING GENERATIVE ARTIFICIAL INTELLIGENCE APPLICATIONS

The paper examines the decision-making process, that the designer and GAI specialist make during development of illustrations for a board game.

Keywords: board game illustration design; generative artificial intelligence; decision making process; prompts; graphic design; image generation.

Introduction

The rapid development of technologies based on use of artificial intelligence, in particular, the generation of images by text (text-to-image), is changing the way we look at all approaches to design. This applies to design of buildings [1], clothing [2, 3], web design [4], game design [5–7], as well as the design of multimedia or printed publications [8]. A large number of similar studies even allowed to single out a separate branch — generative artificial intelligence technologies (Generative AI — GAI). Undoubtedly, this approach attracts specialists with its almost unlimited creative possibilities, provides many options for consideration, and ensures a reduction in time for creating artistic solutions. But, along with such unconditional advantages, generative services are marked by certain significant disadvantages: requests for networks are formulated in the form of texts of limited volume, which requires the graphic designer to work in the unusual field of creating a concise narrative. To generate an image, designer need to set and change a significant number of parameters describing the generative network architecture and its operation process. Not being specialists either in writing or in artificial intelligence, specialists from other fields have to spend a lot of time organizing the design process using generative service, checking a large number of created options, looking for the most satisfactory ones. Sometimes satisfactory samples have to be edited further, because they do not fully meet the designer requirements. In order to most effectively use the advantages of generative networks, and to reduce the impact of negative aspects of their use, it is necessary to develop a certain creative search strategy, which will consist of separate clearly defined steps for configuring network parameters, certain unambiguous rules for formulating prompts to generative service, and develop the sequence of decision-making from step to step during interaction with generative service.

Modern generative services for editing or creating images, videos and 3D models implement the approach of generating a multidimensional result based on a one-dimensional text sequence, submitted to service in a task description form — a prompt. The prompt is built according to certain recommendations, contains several basic elements, that accelerate the creation of most acceptable result and increase its quality. It is clear, that by adjusting these elements, generation of result can be carried out as an iterative procedure.

The main goal of this work is to develop the decision-making sequence for process of image generation using generative artificial intelligence for cardboard game artworks design.

The main goal can be achieved on the basis of studying the principles of generative neural networks functioning, the rules for building text prompts for generating images based on descriptions, studying the requirements for artwork design.

Methods

1.1. GAI text-to-image models

Content generation technologies are developed for several basic types of tasks: natural language generation, image generation, multimodal generation (generation in multimodal machine learning). The main feature to classify them: unimodal models receive input instructions of the same modality as the expected result (example — text generation by text instruction, image generation by drawing); multimodal models, on the other hand, can process input instructions in different modalities, and at the output generate a result whose modality does not coincide with the input (example — generation of a program code or a three-dimensional model based on a text description).

Generative Adversarial Networks (GANs) [9] were the first proposal for artificial synthesis of images with objects, and have now gained great popularity in the image generation field. GANs consist of two parts, a generator and a discriminator. The generator tries to learn the statistical distribution of real examples to generate new data, while the discriminator tries to recognize whether the input is from the real data space or not.

Multimodal generation is an important part of modern AIGC. Its goal is to study a model, that generates raw modalities by studying data-driven multimodal communication and interaction. This relationship and interaction between modalities can sometimes be very confusing, making the multimodal representational space difficult to study compared to the unimodal one. However, with the advent of powerful underlying architectures, more and more methods are proposed to solve this problem.

The encoder-decoder architecture is a widely used framework for solving unimodal generation problems in computer vision. In multimodal generation, particularly in visualization language generation, this method is often used as the underlying architecture. The encoder is responsible for learning a contextualized representation of input data, while decoder is used to generate raw modalities, that reflect cross-modal interactions, structure, and coherence in the representation.

Diffusion-based decoders. Generative imaging has recently seen great success using diffusion models. These models have also been used to create text-to-images. Diffusion models are trained by adding noise to input images, that match textual descriptions. This part is called direct diffusion. At the second stage, the model tries to create an image from the initial noise process, gradually removing the noise. This is reverse diffusion. The initial noise state for back diffusion (seeds) can affect the final result of the generation.

The first element — the variational autoencoder — compresses the input images to the so-called latent (hidden) space. This allows to determine the most characteristic features of images. Direct diffusion is also performed here — Gaussian noise is added to image. The second element is the U-Net — neural network learned how to denoise the original signal from direct back-diffusion to image to find the latent representation. The third element is output VAE decoder, which creates a final image consisting of pixels from the hidden representation. The advantage of LDM is that the training of the second element, the network, can be tuned according to text strings, meaning, that noise overlay is now associated with text instructions.

The main difference between diffusion-based models and previous generative methods is that diffusion-based models are usually trained on a larger data set with a much larger number of parameters, allowing for better representations to be learned compared to others.

1.2. Rules for creating prompts as a means of image generation managing

Generative services use textual instructions called prompts as input to create images. The prompt consists of several optional elements:

— instructions are a task, that the model must perform;

— context — external information or additional information, that can direct the model to more accurate answers;

— input data — a task or question for which necessary to find an answer;

— output indicator — the type or format of finished result output.

The prompt details directly affect the generation output, but they should also have some limits. So, it may turn out, that the initially compiled prompt does not give the desired result, then it has to be changed — this process is iterative. It is possible to reduce its duration and achieve high-quality results by using certain principles of creating prompts — Prompt Engineering.

Many sources with instructions for creating prompts when interacting with GAI systems [10–13] recommend formulating the context using elements such as modifiers. Most often, modifiers add certainty in such features as:

— format and appearance of the result (photo, pencil drawing, oil painting, watercolor, wood, clay, etc.);

— parameters characterizing photography (type of camera plan, style, lighting, perspective, type of lens and camera);

— artistic style (portrait, landscape, horror, anime, science fiction, concept art for video games, a mixture of styles, etc.);

— type of illustration (children's book, vector image, comic, caricature, poster, movie poster, psychedelic art and others);

— emotional signs (alive, energetic, colorful, carefree, sophisticated, ethereal, gloomy, stormy, fatal, sad, pale, tired);

— signs of size and structure (large, chaotic, small, rectilinear);

— image resolution.

Obviously, the artworks development will require the designer to know a sufficiently large number of modifier words, that describe listed features, as well as to understand how certain modifier words can be related to each other (for example, an anime art style may require an emotional modifier 'carefree, romantic, joyful', and is unlikely to be combined with the modifiers 'mourning, boring, depressed').

In addition to initial data entering the generative service in the form of prompts, it is necessary to set several values of working settings for architecture, which may differ slightly for each service. For example, these are the steps setting, the classifier free setting (Classifier Free Guidance CFG), the sampling setting (sampler), the temperature (temperature), the model (model), the clip guidance scale (Clip Guidance Scale CGS), the initial noise values (seed), result detail settings (cut_ic_pow), settings for the organization of packages for network learning (batch, cutn batch), settings for increasing contrast, color saturation (clamp_max), a switch for symmetry of objects (symmetry switch), etc.

So, one cannot help, but conclude, that generate the image required for a certain publication design task, designer has to randomly solve the optimization problem in multidimensional search space.

1.3. Design approaches using GAI

Since GAI is potentially able to provide unique graphical artifacts for a variety of tasks, it is necessary to define the main properties of this tool as a component of print or multimedia content development technologies.

Many researchers have already considered how to solve the task of finding the optimal design in the multidimensional space of possible solutions provided by GAI systems [14–16]. It is noted, that architectures, which are the basis for generative services, are probabilistic in nature, and are focused on issuing a significant number of possible results. Generative variability ensures the uniqueness of received answers, even under the condition of complete identity of prompts and settings at the GAI system input [16].

The paper [2] proposes a classification of all possible scenarios of interaction between a fashion designer and a generative service. This classification contains five possible scenarios (in the article they

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are called interaction patterns): system organization (Curating), research (Exploring), evaluation (Evolving), adding conditions (Conditioning), rewriting (Rewriting). These scenarios include 7 main operations of interaction of the designer with the GAI system (fig. 1): Initialize; Learn; Constrain; Create; Select; Adapt; Combine.

Generative systems, unfortunately, cannot process the created images, cannot improve the result in an iterative built-in process, cannot remember the user's wishes. The scenarios proposed in [2] allow overcoming these difficulties thanks to cooperation with the designer.

When creating illustrative content, the designer does not always know in advance which artistic style and appearance will work best, so he or she must first make several trial generations, implementing the research scenario. Within this study, designer sets system settings by choosing model type, method of samples selecting for learning, number of steps, classifier setting scale, etc.

A simple prompt without samples (zero-shot prompt) is created, and negative prompts are also added to ensure the believability of depicted objects. After generation starting, the designer evaluates how well the obtained results correspond to the task and makes adjustments to network settings, to positive and negative feedback. Thus, the first stage of research includes several actions that are repeated iteratively: Initialize; Learn; Constrain; Create; Select; Adding constraints — as a negative prompt task — now precedes model training.

The research stage allows to generally find a color solution and some nuances of appearance (photo, drawing, etc.). Such results may be satisfactory if initially the task involved a significant degree of uncertainty about how the illustration should look. But it often happens, that the creative task is very narrowly specified. Undoubtedly, this specification makes it possible to more accurately formulate a prompt for generations, but selection of model settings still has to be carried out anew every time. In addition, for certain illustrations, sometimes even the object pose can be rigidly specified, then during design creation it is necessary to connect the stage of adding conditions, which is also implemented using a generative model (fig. 1).

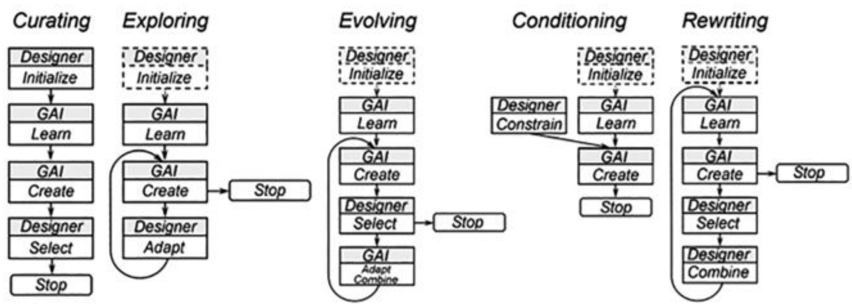

Fig. 1. Basic scenarios of interaction of the designer with the GAI system [2]

Some generative services already have image editing tools, that allow to color individual elements, add blur without changing the illustration main content, and preserve the artistic style. Using the set of basic actions defined above, it can be concluded, that editing and partial improvement of generated image will be carried out during the evaluation phase by means of such actions as adaptation and combination. Combining is performed to merge object pose generated in the condition addition step with most acceptable result of the exploration step. After combining, there is adaptation, that is, improvement of illustration using editing tools during the evaluation phase. Thus, the general diagram of technology for developing the artwork illustrations design for cardboard games can be presented in fig. 2.

Results

The proposed on fig. 2 technology of illustrations developing was investigated for the task of creating a design of a board game in the style of 'cyberpunk'. Stable Diffusion WebUI Automatic1111 generative service was chosen and deployed on Acer Nitro 5 17'3 laptop, Geforce RTX 3070TI 8gb, 32 gb RAM, I-7 12700H, 1TB SSD. The main design idea was to develop playing cards, where the faces look like

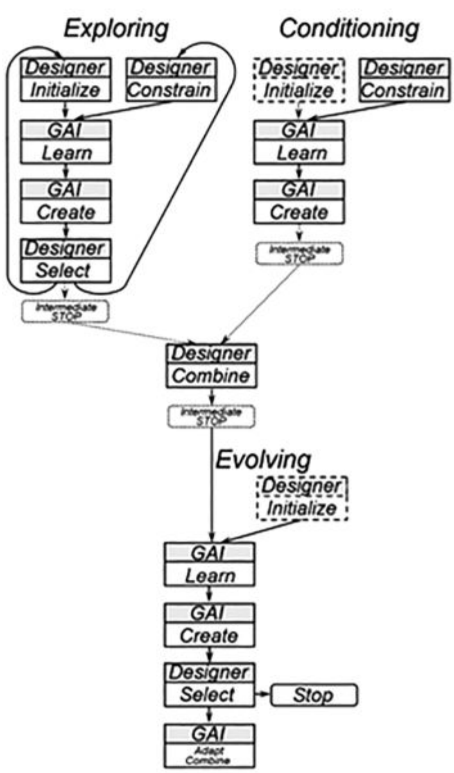

Fig. 2. The proposed diagram of the technology developing the artwork illustrations design for cardboard games

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Fig. 3. Result of illustration generation by prompt without sample, the design includes only the exploring stage without adding constraints

color photos in the style of cyberpunk, the suits are distinguished by four colors, with which the same elements in different suits must be painted.

So, it is obvious, that the development should consist of several main project stages:

— exploring;

— combination of exploring, conditioning and evolving.

The main goal of the first stage of curation or research is to find a generation model, that will best produce a given visual style. For process according to diagram in fig. 3 the settings given in table 1 were selected.

The result was an image, that was negatively evaluated by the designer (fig. 3): illustration style does not correspond to definition

Table 1

Settings for the Stable Diffusion WebUI Automatic1111 generative service to create a board game artwork in one step Prompted exploring without samples

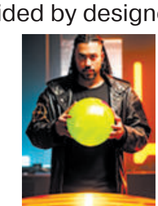
Action	Settings	Value
Initialization	Model	Lyriel_v16
	Zero-shot prompt	*man in neon blue jacket, sci-fi clothes, mature, (futuristic:1.2), cyberpunk*
	Illustration size	512×712
	Sampling Method	DPM++ 2M Karras
	Sampling steps	50
	CFG Scale	By default 7
	Seed	1688159780 After several iterations
Added restrictions	Negative Prompts	*dof, grayscale, black and white, bw, 3d, cartoon, anime, sketches, (worst quality:2), (low quality:2), (normal quality:2), lowres, normal quality, ((monochrome)), ((grayscale)), skin spots, acnes, skin blemishes, bad anatomy, girl, loli, young, large breasts, red eyes, muscular, bad-handsv5-neg, By bad artist-neg (1), monochrome, nsfw*

of 'cyberpunk', the man is very old, the clothes do not correspond to the style, the background does not correspond to the style. As positive result can be considered the conclusion, that the chosen model is not able to generate the given style. After that, it was decided to change the generation model, change the prompt and supplement the image with additional conditions regarding character pose and presence of one more object (sphere) in image.

The task from the designer was more specific, it was necessary to create a portrait of a person who would fit the name 'Cyber King' and hold a bright sphere in his hands in the center of the image. At this step, the design process is carried out according to the diagram in fig. 2, the process includes the stages of exploring, conditioning and evolving. Settings of generative system are given in table. 2.

Table 2

Setting up the Stable Diffusion WebUI Automatic1111 generative service to create a board game illustration in three steps Exploring, Conditioning, Evolving by prompt without samples (settings of first two stages are given)

Action	Settings	Value
	Exploration	
Initialization	Model	Reliberate_v10
	Zero-shot prompt	*king, cyberpunk, holding the sphere, old man, neons, long beard*
	Illustration size	512×712
	Sampling Method	DPM++ 2M Karras
	Sampling steps	20
	CFG Scale	By default 7
	Seed	1050799033 After several iterations
Added restrictions	Negative Prompts	*female, low quality, worst quality, bad anatomy, bad hands, mutated, fewer digits, extra digits, (worst quality:1.2), (low quality:1.2), (lowres:1.1), (monochrome:1.1), (greyscale), multiple views, comic, sketch*
	Conditioning	
Initialization of ControlNet application	Few-shot prompt	The prompt for system learn is a pose image provided by designer 
Learning	OpenPose	OpenPose_Full

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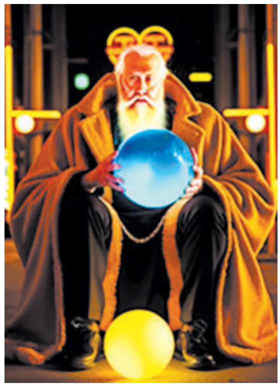

Fig. 4. An intermediate result of the generation of the illustration for the two stages of Exploring, Conditioning with prompt adding

As an intermediate result, an illustration was obtained (fig. 4), regarding which the designer's comments were unsatisfactory: the character's pose, age, and upper sphere are on point, but the character's clothing is off. Instead of lower sphere, there should be a crown.

To change the character's clothes and add the crown, the corresponding hints were created in the third stage of design creation. The settings are given in the table 3.

According to the results of this stage, the designer's comment improved: 'Almost everything corresponds to task, instead of yellow sphere at the bottom, must be a crown' (fig. 5).

The last improvement is aimed at creating a detailed image of the crown, which will indicate the rank on the game map. For this element, it is no longer necessary to start the design from the beginning, it is enough to add another iteration to the evaluation stage. The service settings are listed in the table 4, the result of the iteration is shown in fig. 6.

Table 3

Settings of the Stable Diffusion WebUI Automatic1111 generative service to create a board game illustration in the three stages of Exploration, Conditioning, Evaluation by prompt without samples (settings of the third stage are shown)

Action	Settings	Value
Initialization of Stable Diffusion in Inpaint mode	Model	RevAnimatedInp
	Prompts	*standing, king, cyberpunk, holding the sphere, old man, neons*
	Sampling Method	DPM++ 2M Karras
	Denoising Strength	1.0
	Seed	3263849708
Added restrictions	Negative Prompts	*female, low quality, worst quality, bad anatomy, bad hands, mutated, fewer digits, extra digits, (worst quality:1.2), (low quality:1.2), (lowres:1.1), (monochrome:1.1), (greyscale), multiple views, comic, sketch*

Fig. 5. The result of the generation of the illustration for the third stage of Evaluation by prompt without samples

Fig. 6. The result of the generation of the illustration for the third stage of Evaluation by prompt without samples (iteration 2)

The designer noted, that the background does not correspond to cyberpunk style, the sphere is too small and is not located in the middle of image, the crown color does not match image gamut, the crown is dull, the character is not associated with the image of the King.

So, despite the obvious progress in generation of illustration

Table 4

Configuration of the Stable Diffusion WebUI Automatic1111 generative service to create an illustration for a board game in the three stages of Exploration, Conditioning, Evaluation by prompt without samples (iteration 2 of Evaluation by prompt without samples stage)

Action	Settings	Value
Initialization of Stable Diffusion in Inpaint mode	Model	RevAnimatedInp
	Prompts	*crown*
	Sampling Method	DPM++ 2M Karras
	Denoising Strength	0.7
	Seed	1209726908
Added restrictions	Negative Prompts	female, low quality, worst quality, bad anatomy, bad hands, mutated, fewer digits, extra digits, (worst quality:1.2), (low quality:1.2), (lowres:1.1), (monochrome:1.1)
	PhotoPea App	
	Inpaint Area	Only Masked

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artwork, the designer had to manually bring the image to desired condition: paint the background, add game marks to cards and change the coloring of image elements according to game marks (fig. 7).

Discussion

Based on results of experimental study, it can be established, that generative service performs designer's task to create illustrations for cardboard game effectively enough. Another finding is that the designer inconsistently creates prompts that, at several design steps, do not meet the designer's requirements present in estimates. Obviously, in order to improve the efficiency of using generative systems when creating illustrative content, designers need to record prompts and their own evaluations of obtained results at each step to coordinate evaluation criteria and instructions for system.

Fig. 7. The final result of image design for cardboard game after the designer's finishing touches

Artificially generated images can be used as a basis for further design refinement, if certain changes are made to diagram of the illustration development process, adding adaptation and combination actions at evolving stage, which are performed not only by automatic system, but also by designer manually (fig. 8).

In addition, some feedback needs to be added based on selection of acceptable design options in Evaluating stage, after which it may be necessary to revert either to editing images using generative system in Evaluating stage, or changing prompts and re-generating it at the same Evaluating stage, or at all, to return to the very beginning of design process to Exploring stage to initiate generation with a new model, with new settings, with new prompts.

Conclusions

The paper considers the problem of decision-making in process of board games artwork design using generative artificial intelligence systems. The nature and sequence of steps of interaction between a designer and a GAI specialist during illustrative content development are considered. Based on the established features, several typical interaction scenarios have been modified: Exploring scenario, Conditioning scenario, Evolving scenario. For individual actions combined by these scenarios, a certain order was established, the addition of feedback links between actions of individual scenarios was pro-

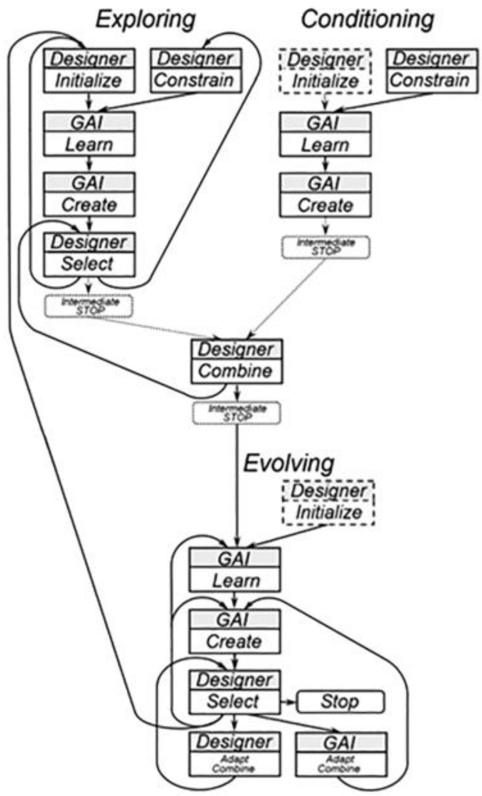

Fig. 8. Scheme of the technology of board games artwork design, including images finishing by designer manually

posed. Introduced feedbacks made it possible to create a continuous three-stage scheme of board games artwork design using generative systems.

The conducted experiment confirmed the effectiveness of developed scheme and added recommendations for a more accurate formulation of text instructions to generative system. The proposed approach makes it possible to significantly speed up designer's work when designing the illustrative content of publications, and to improve the quality of unique creative content.

References/Список використаної літератури

1. Chen, R., Zhao, J., Yao, X., Jiang, S., He, Y., Bao, B., Luo, X., Xu, S., & Wang, C. (2023). Generative Design of Outdoor Green Spaces Based on Generative Adversarial Networks. *Buildings*, 13, 1083. https://doi.org/10.3390/buildings13041083.

2. Grabe, I., & Zhu, J. Towards Co-Creative Generative Adversarial Networks for Fashion Designers. *arXiv:2304.09477v1*. https://doi.org/10.48550/arXiv.2304.09477.

3. Kulkarni, C., Druga, S., Chang, M., Fiannaca, A., Cai, C., & Terry, M. (2023). *A word is worth a thousand pictures: Prompts as ai design material*.

ISSN 2077-7264. Технологія і техніка друкарства. 2024. № 1(83)

4. Kikuchi, K., Inoue, N., Otani, M., Simo-Serra, E., & Yamaguchi, K. (2023). Generative Colorization of Structured Mobile Web Pages. *2023 IEEE/CVF Winter Conference on Applications of Computer Vision (WACV)*, 3639–3648. doi 10.1109/WACV56688.2023.00364.

5. *ConvAI. Convai — Conversational AI for Virtual Worlds — convai.com*. Retrieved from https://www.convai.com/ [Accessed 17 May 2023].

6. *CSM. CSM AI — 3D World Models — csm.ai*. Retrieved from https://csm.ai/ [Accessed 17 May 2023].

7. *PixelVibe. Create Gaming Assets Using AI: PixelVibe by Rosebud AI — pixelvibe.com*. Retrieved from https://www.pixelvibe.com/ [Accessed 17 May 2023].

8. Kong, X., Jiang, L., Chang, H., Zhang, H., Hao, Y., Gong, H., & Essa, I. BLT: Bidirectional Layout Transformer for Controllable Layout Generation. *arXiv:2112.05112v2*. https://doi.org/10.48550/arXiv.2112.05112.

9. Goodfellow, I. J., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., Courville, A., & Bengio, Y. (2014). *Generative adversarial networks.*

10. Rombach, R., Blattmann, A., Lorenz, D., Esser, P., & Ommer, B. (2022). High-Resolution Image Synthesis with Latent Diffusion Models. *Proc. International Conference on Computer Vision and Pattern Recognition (CVPR)*. New Orleans, LA, 10684–10695. arXiv:2112.10752.

11. Inuwa, M. (2023). *Guide to Image-to-Image Diffusion: A Hugging Face Pipeline*. Retrieved from https://www.analyticsvidhya.com/blog/2023/05/how-to-generate-images-using-stable-diffusion/.

12. *Stable Diffusion Prompt Book*. Retrieved from https://openart.ai/promptbook. [Accessed 17 May 2023].

13. *Prompt book for data lovers.* Retrieved from https://domesticstreamers.com/. [Accessed 17 May 2023].

14. Liao, Q. V., Gruen, D., & Miller, S. (2020). Questi*oning the ai: informing design practices for explainable ai user experiences. Proc. of the 2020 CHI Conference on Human Factors in Computing Systems*, 1–15.

15. Morris, M. R., Cai, C. J., Holbrook, J., Kulkarni, C., & Terry, M. (2022). The design space of generative models. *Proc. of the NeurIPS 2022 Workshop on Human-Centered AI (NeurIPS2022)*.

16. Weisz, J. D., Muller, M., He, J., & Houde, S. (2023). *Toward General Design Principles for Generative AI Applications*. arXiv:2301.05578.

У роботі розглядається процес прийняття рішень, які приймають дизайнер та фахівець GAI під час розробки ілюстрацій до настільної гри.

Ключові слова: дизайн ілюстрацій настільних ігор; генеративний штучний інтелект; процес прийняття рішень; підказки; графічний дизайн; генерація зображень.

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