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Automated Social Media Advertising Poster Design Using a Multi-Agent AI Framework

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ABSTRACT

This study proposes an automated system for social media advertising poster generation using a role-based multi-agent architecture implemented with CrewAI. The system decomposes the design task into three sequential agents responsible for text generation, visual asset recommendation, and grid-based layout optimization. A formal 12×12 discrete layout model is employed to represent spatial constraints, enabling consistent and structured poster composition. System performance was evaluated through user testing involving five respondents using a five-point Likert scale. The results show mean scores of 3.2 for content completeness, 3.6 for layout consistency, 3.8 for text relevance, and an overall performance mean of 3.4 (SD = 0.15), indicating satisfactory usability. From an applied mathematics perspective, this work contributes a computational layout formulation using grid discretization and rule-based optimization, as well as a quantitative evaluation of multi-agent coordination efficiency. The proposed framework demonstrates that agentic AI can effectively support structured visual content generation while maintaining user-controlled refinement.

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1. INTRODUCTION

The rapid development of artificial intelligence (AI) has enabled automated systems for visual content generation, particularly in digital advertising and social media design. From a computational perspective, poster design can be formulated as a structured layout optimization problem, where textual and visual elements must be arranged under spatial, aesthetic, and semantic constraints. Recent advances in large language models (LLMs) have demonstrated strong capabilities in instruction understanding and multi-step reasoning, enabling their integration into complex decision-making pipelines, including multi-agent systems [1], [2].

In social media advertising, effective poster design requires the coordination of multiple variables, such as content relevance, visual balance, and spatial consistency. For small and medium-sized enterprises (SMEs) and individual creators, this task is often constrained by limited resources and design expertise. Mathematically, this challenge can be viewed as a constrained placement problem, where multiple design elements compete for limited spatial regions while maintaining layout coherence and readability. Inconsistent or suboptimal layout arrangements may reduce visual quality and audience engagement [5].

Previous studies on automated layout generation have approached this problem using formal mathematical and statistical models. Transformer-based layout graphs model spatial relationships as node-edge structures [6], while GAN-based methods optimize layout aesthetics through adversarial learning [7]. Diffusion-based approaches further introduce probabilistic sampling to generate visually coherent layouts under learned distributions [8]. Poster generation systems such as AutoPoster, PosterLLaVA, and PosterGen extend these models to end-to-end pipelines by combining multimodal inputs and learned layout priors [9]–[11]. Despite their effectiveness, these approaches are typically fully automated, computationally intensive, and offer limited interpretability or user-driven refinement after generation.

Recent work in multi-agent artificial intelligence introduces an alternative paradigm, where complex tasks are decomposed into interacting agents with specialized roles [12]–[14]. From an algorithmic standpoint, multi-agent systems enable modular problem decomposition, reducing complexity by assigning subtasks—such as content generation, visual selection, and layout structuring—to independent but coordinated processes. However, existing studies primarily emphasize architectural design or application-level performance, with limited discussion on explicit spatial modeling or formal layout representations. Moreover, few systems integrate agentic AI with discrete grid-based formulations commonly used in classical layout optimization and graphic design theory.

To address this gap, this study proposes a CrewAI-based multi-agent framework that formalizes poster layout generation using a discrete 12×12 grid model. Each poster component is represented as a bounded region within the grid, transforming layout generation into a constrained spatial assignment problem governed by alignment rules and placement constraints. Unlike prior GAN-, diffusion-, or transformer-based models that learn layout distributions implicitly, the proposed approach introduces an explicit and interpretable layout formulation that supports deterministic rendering and post-generation refinement. Quantitative evaluation using user-based scoring further provides descriptive statistical evidence of layout consistency and usability.

The main contribution of this work lies in bridging agentic AI with a formal grid-based layout representation, offering a computationally efficient and interpretable alternative to fully learned layout models. By combining multi-agent coordination with discrete spatial modeling, the proposed system demonstrates a mathematically grounded approach to automated poster generation that balances algorithmic structure, user control, and practical applicability for SMEs, content creators, and educational environments.

2. RESEARCH METHOD

2.1 Agent Design in CrewAI

The system design in this study is based on the use of CrewAI as a multi-agent framework to coordinate multiple Large Language Model (LLM)-based agents within a single structured workflow. CrewAI provides an orchestration mechanism that enables agents with predefined roles to collaborate while performing specialized tasks independently [13], [15] In this framework, user instructions are decomposed into smaller subtasks and assigned to the appropriate agents according to their respective responsibilities. Each agent functions as an independent processing unit capable of analysis, output generation, and inter-agent communication, allowing the overall workflow to operate in a coordinated and sequential manner. From a computational perspective, this orchestration can be viewed as a modular task-decomposition strategy, where a complex design problem is split into simpler subproblems handled by specialized agents. The general CrewAI workflow employed in this study is illustrated in figure 1.

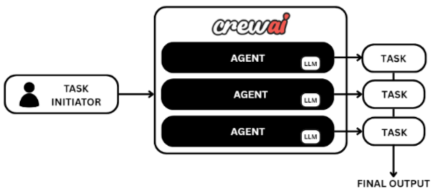

Figure 1. Workflow of the CrewAI-Based Agentic AI System

Based on this architecture, the system implements three main role-based agents specifically designed for social media advertising poster creation. The agents are organized according to the principle of task specialization, where each agent focuses on a distinct aspect of the design process while complementing the outputs of the others. This role separation reduces computational complexity at each stage and improves interpretability compared to monolithic generative pipelines. This role-based multi-agent design enables the poster production process to be executed end-to-end, from content generation to visual composition and layout structuring.

2.2 Factual Agent

The Factual Agent is responsible for generating fact-based textual content related to the product being advertised. Its primary objective is to produce concise, clear, and persuasive advertisement titles and descriptions that can be directly used as poster copy. This agent utilizes the GPT-4o-mini model through the LangChain framework to process user input and extract essential product information, such as product type, key features, and target audience.

```
factual = Agent
        role="Factual Agent",
        goal="Create short, clear ad copy.",
        backstory="Writes clean titles /
        taglines.",
        allow_delegation=False,
```

Figure 2. Role Based Factual Agent

By leveraging the natural language understanding capabilities of LLMs, the Factual Agent summarizes this information into short and effective advertising text. To ensure consistency and reproducibility, the agent operates under a fixed prompt template and constrained output length, with deterministic decoding parameters applied during generation. The generated output serves as the main textual component of the poster. The role-based configuration of the Factual Agent is shown in Figure 2.

2.3 Visual Agent

The Visual Agent is tasked with generating visual concepts and identifying suitable image sources to support the advertisement. Its goal is to produce image search queries that align with both the product characteristics and the desired visual style of the poster. This agent translates user prompts and the textual output from the Factual Agent into relevant image queries by analyzing factors such as product category, color palette, and stylistic preferences (e.g., minimalist, pastel, or sporty).

```
visual = Agent
        role="Visual Agent",
        goal="Suggest produt and background image queries.",
        backstory="Image query specialist.",
        allow_delegation=False,
        llm=llm,
```

Figure 3. Role Based Visual Agent

The queries are then used to retrieve images from external sources through the Unsplash API. From a system modeling standpoint, this step can be interpreted as a retrieval-based matching process that maps semantic keywords to candidate visual assets rather than generating images probabilistically. By acting as a bridge between textual content and visual assets, the Visual Agent ensures that the selected imagery supports the advertising message. The role-based configuration of the Visual Agent is illustrated in Figure 3.

2.4 Layout Agent

The Layout Agent is responsible for designing the structural layout of the advertising poster. Its primary task is to generate a layout scheme in JSON format that is compatible with the system's grid-based design framework. The agent employs the GPT-4o-mini model to define the spatial arrangement of poster components, which is then processed by a Python-based grid layout rendering module implemented using the Python Imaging Library (PIL).

```
layout = Agen
        role="Layout Agent",
        goal="Return EXACT JSON layout schema.",
        backstory="Grid layout master.",
        allow_delegation=False,
        llm=llm,
```

Figure 4. Role Based Layout Agent

The generated layout scheme specifies the position of each component—including the title, main image, description, and logo—based on a predefined 12×12 grid system. Formally, each component is represented as a bounded rectangular region defined by grid coordinates and dimensions, ensuring that all elements lie within the poster domain and follow non-overlapping placement rules. The scheme also includes alignment settings and display properties, such as image scaling modes. The output of the Layout Agent is subsequently used by the rendering engine to place visual elements consistently on the poster canvas. The role-based configuration of the Layout Agent is shown in Figure 4.

2.5 Flowchart System

The workflow of the poster creation system in this study is designed to process user instructions sequentially through the collaboration of three main agents: the Factual Agent, Visual Agent, and Layout Agent. Each agent performs a specific role in generating different components of the advertisement, ranging from composing textual content and selecting visual assets to designing the poster layout structure. The outputs produced by these agents are subsequently integrated and rendered into an initial poster draft that can be reviewed and refined by the user. The overall system workflow, from user input to the final downloadable advertisement poster, is illustrated in Figure 5.

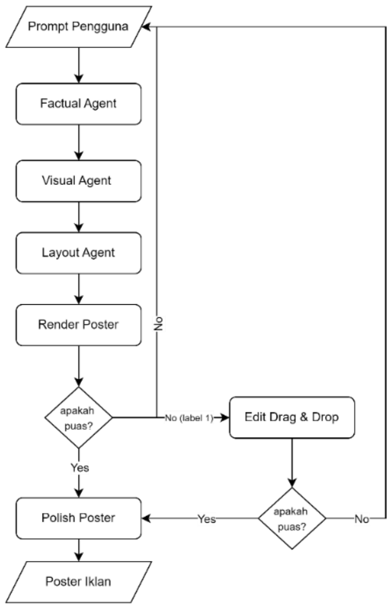

Figure 5. Flowchart System

The workflow begins when the user provides a product prompt and layout instructions through the application interface. These inputs are forwarded to the run crewai() function, which orchestrates the execution of the three agents within the CrewAI framework. A role-based multi-agent approach is adopted, in which the same underlying LLM is used across agents while each agent is assigned a distinct functional role, a strategy commonly employed in contemporary multi-agent system research [2], [13]. The first stage is carried out by the Factual Agent, which generates advertising text in the form of concise product titles and descriptions. This agent leverages the language comprehension capabilities of LLMs to summarize user-provided product information into relevant and persuasive textual content [1].

In the subsequent stage, the Visual Agent generates image search queries based on the user prompt and the textual output produced by the Factual Agent. These queries are used to retrieve relevant product and background images from external image providers such as Unsplash. This retrieval-based approach is consistent with prior research in automated poster and visual content generation, including systems such as AutoPoster and PosterLLaVA [9], [10] Following this step, the Layout Agent produces a layout structure in JSON format using a predefined 12×12 grid system. This grid-based representation introduces an explicit spatial model that supports deterministic rendering and post-generation refinement, unlike implicit layout representations learned in GAN- or diffusion-based approaches. The generated layout defines spatial regions for poster components, including the title, main image, description, and logo. This grid-based representation aligns with established layout generation methods based on transformer and GAN architectures [6], [16].

After all agents complete their respective tasks, their outputs are combined and passed to the render_from_grid() function. This rendering module initializes a poster canvas, computes grid cell dimensions, places each component according to the layout specification, and generates an initial poster preview. The preview is then presented to the user for evaluation. If the user is not satisfied with the result, the system provides an interactive drag-and-drop editing mode that allows elements to be repositioned directly on the canvas. This refinement process preserves the underlying grid structure while allowing user-driven local adjustments. Such interactive refinement mechanisms have been shown to support user control and improve usability in AI-assisted design systems [5], [17].

Once the user completes the manual adjustments, the poster is re-rendered and can proceed to a polishing stage, where visual attributes such as contrast, lighting, and texture may be adjusted. If the user is satisfied with the final output, the poster can be downloaded along with its corresponding JSON layout file. Alternatively, the user may return to the initial stage to modify the prompt or visual assets, enabling an iterative and flexible design workflow.

3. RESULT AND ANALYSIS

3.1 Result

To demonstrate the system's output, a test was conducted using a sample input provided by the user. The product prompt "Create an ad for women's cotton shirt (S–XL), pastel color palette" was combined with the layout instruction "Image on center. Title centered. Put the logo on the center", along with a logo URL. Based on this input, the system generated an advertising poster through the sequential execution of the Factual Agent, Visual Agent, and Layout Agent. The initial layout was subsequently refined using the drag-and-drop adjustment feature, followed by a polishing step to enhance visual quality. The final poster produced by the system is shown in Figure 6.

Figure 6. Final Poster

The final poster reflects the complete system workflow, including both automated generation and manual refinement performed by the user. Although the initial layout was generated according to the user's prompt, the drag-and-drop feature allows users to reposition elements freely, which may result in a layout that differs from the original instruction. This behavior demonstrates that the system not only automates the core poster design process but also provides flexibility for user-driven customization. At this stage, the visual simplicity of the poster is not intended as an aesthetic benchmark; rather, the primary objective is to verify the functional correctness of each agent and the coherence of the resulting poster layout.

Figure 7. Drag and Drop Result

The grid-based guideline boxes displayed in Figure 7 represent the layout regions used during the refinement stage. These boxes visualize the underlying 12×12 discrete grid structure generated by the Layout Agent, where each poster component such as the title, product image, and logo is assigned a specific spatial region. During the drag-and-drop editing process, these guidelines help users understand element positioning while ensuring that manual adjustments remain aligned with the system's structural design principles.

A user-based evaluation was conducted involving five respondents (R1–R5) who had basic familiarity with graphic design, digital content creation, or small-scale promotional activities. Some respondents were small business owners accustomed to producing simple advertising materials for their products. The evaluation aimed to assess the quality of the generated posters in terms of content completeness, layout consistency, text relevance, image suitability, and overall system performance. All assessments were conducted using a five-point Likert scale (1 = very dissatisfied, 5 = very satisfied). The evaluation results are summarized in Table 1.

Table 1. Respondent Evaluation Results

No	Respondents	Content	Layout	Text	Image	CrewAI Performance	Overall Performance
1	R1	3	3	4	2	4	3.2
2	R2	2	4	4	3	4	3.4
3	R3	3	4	3	3	4	3.4
4	R4	3	4	4	3	4	3.6
5	R5	3	3	4	3	4	3.4

Across all respondents, the mean Overall Performance score was 3.4 with a standard deviation of 0.15, indicating moderate variability and consistent user perceptions within this small sample. Overall, the system achieved average scores above the midpoint of the Likert scale across all evaluated criteria, indicating satisfactory performance for an initial usability-oriented evaluation.

In addition, the proposed system was descriptively compared with two widely used AI-based content generation tools, ChatGPT and Gemini. This comparison is descriptive in nature and is not intended as a controlled experimental evaluation. This comparison was intended to illustrate differences in workflow characteristics, flexibility, and output stability rather than to serve as a controlled experimental benchmark.

Table 2. Average Respondent Scores

No	Aspects	CrewAI (built system)	ChatGPT	Gemini
1	Price	Free	Subscription	Subscription
2	Flexibility	Very flexible (multi-agent)	Limited on conversation	Limited on conversation
3	Execution Time	Fast (24 seconds)	Not So Fast (1 minute)	Fast (30 seconds)
4	Memory	Good, the image does not change	The image changes because it's generative	The image changes because it's generative
5	Reasoning Multi-step	Very Compatible	Compatible Enough	Compatible Enough
6	Logo Compatibility from Links	Compatible	Not Compatible	Not Compatible
7	Suitable for Poster Making	Yes, Very Suitable (multi-agent)	Less structured	Less structured
8	Ease of Use	Initial training needed	Very Easy	Very Easy

Because the tools differ in interface design, prompt handling, and user familiarity, the comparison results may be influenced by confounding factors and should be interpreted cautiously. The findings are therefore framed as exploratory observations rather than evaluative benchmarks. Based on the comparison presented in Table 2, several observations can be drawn across the evaluated aspects. In terms of cost, the proposed CrewAI-based system does not require additional subscription fees, whereas ChatGPT and Gemini rely on paid access for comparable generative features. Regarding flexibility, the proposed system provides greater configurability through its role-based multi-agent workflow, while ChatGPT and Gemini operate primarily through conversational interactions with limited structural control.

In terms of execution time, the proposed system generates poster outputs within a comparable or slightly faster timeframe than the two conversational AI tools. With respect to output stability, the CrewAI-based system maintains more consistent visual structures and image placements due to the use of cached processing and JSON-based layout representation, whereas ChatGPT and Gemini tend to produce variable images and layouts across iterations. For multi-step reasoning, the separation of responsibilities among agents enables a more structured reasoning process, while conversational models do not explicitly support role-based reasoning workflows.

Additionally, the proposed system demonstrates better compatibility when incorporating external logo assets, as logos can be retrieved and positioned without modification, whereas ChatGPT and Gemini may alter or inconsistently handle user-provided logo inputs. Overall, the comparison suggests that the proposed multi-agent system is more suitable for structured advertising poster creation, while ChatGPT and Gemini offer greater ease of use for general users due to their conversational interfaces. These findings highlight trade-offs between usability and structural control rather than definitive performance superiority.

3.2 Discussion

The results of this study indicate that the proposed CrewAI-based multi-agent system is capable of generating advertising posters that are structurally coherent and functionally usable. User responses related to content completeness, layout consistency, and text relevance suggest that role separation among agents supports a more organized and systematic generative process. This observation is consistent with prior studies showing that multi-agent architectures can enhance consistency and reasoning in automated design tasks [2], [12].

Variations in image-related scores can be attributed to the reliance of the Visual Agent on external image retrieval sources, where image relevance and quality may vary. Nevertheless, the integration between the Visual and Layout Agents produced visually acceptable compositions, supporting existing research that emphasizes the importance of grid-based layout representation in maintaining visual regularity [6], [7]. The inclusion of simple grid-based metrics further demonstrates that layout quality can be analyzed quantitatively using the proposed discrete representation.

The descriptive comparison with ChatGPT and Gemini highlights differences in flexibility, workflow structure, and layout stability. Unlike conversational generative models that tend to produce variable outputs across iterations, the proposed system maintains structural consistency through explicit agent coordination and JSON-based layout control. The inclusion of a drag-and-drop refinement feature further enhances user control by allowing iterative adjustments without restarting the generation process.

3.3 Limitations

This study has several limitations that should be acknowledged. First, the evaluation involved a small, non-random sample, which limits external validity and generalizability. Second, although basic measures of variability were introduced, the analysis did not include inferential statistical testing, and therefore the results should not be interpreted as evidence of statistical superiority. Third, the comparison with other AI tools was descriptive and did not control for confounding factors such as interface design, prompt interpretation, or user familiarity. Consequently, the findings should be interpreted as preliminary evidence of system usability and functional feasibility rather than proof of broad effectiveness. Future work will involve larger and more diverse user samples, controlled experimental designs, and objective performance metrics to strengthen evaluation validity.

4. CONCLUSION

This study proposes a CrewAI-based multi-agent framework for automated social media advertising poster generation, integrating content creation, visual asset selection, and grid-based layout modeling within a unified workflow. By adopting an explicit 12×12 discrete grid representation, the system enables deterministic layout generation, interpretability, and post-generation user refinement, distinguishing it from fully learned GAN-, diffusion-, or transformer-based layout approaches. User-based evaluation results show a mean overall performance score of 3.4 (SD = 0.15) on a five-point Likert scale, indicating consistent and satisfactory usability. Layout consistency and structural coherence were positively rated, while image-related variability was mainly influenced by external retrieval sources. Basic grid-level analysis confirms non-overlapping placement, consistent alignment, and balanced spatial utilization, demonstrating that the proposed discrete representation supports objective structural assessment.

From an applied mathematics perspective, the contribution of this work lies in formulating poster layout generation as a constrained spatial assignment problem embedded in a multi-agent coordination framework. Each design element is modeled as a bounded region within a discrete grid, providing an interpretable and computationally efficient alternative to implicit learned layout distributions. The system prioritizes feasibility, reproducibility, and user control rather than global aesthetic optimization. Beyond its practical application, the proposed framework serves as a testbed for future mathematical modeling of multi-agent systems and layout generation. Future work may extend this approach through optimization-based layout selection, probabilistic modeling of user preferences, formal layout quality metrics, and deeper analysis of agent interaction dynamics. Although limited by sample size and descriptive evaluation, this study establishes a mathematically grounded foundation for further research at the intersection of agentic AI, layout modeling, and applied mathematics.

5. REFERENCES

[1] T. Eloundou, S. Manning, P. Mishkin, and D. Rock, “GPTs are GPTs: An Early Look at the Labor Market Impact Potential of Large Language Models,” Mar. 2023, [Online]. Available: http://arxiv.org/abs/2303.10130

[2] T. Guo et al., “Large Language Model based Multi-Agents: A Survey of Progress and Challenges,” Apr. 2024, [Online]. Available: http://arxiv.org/abs/2402.01680

[3] N. Bonafix, O. Frans, N. Latif CM, and Ardiyan, “ANALISIS PENGGUNAAN ARTIFICIAL INTELLIGENCE SEBAGAI BAGIAN DARI SEBUAH KARYA VISUAL MULTIMEDIA,” INFOTECH journal, vol. 10, no. 2, pp. 333–342, Dec. 2024, doi: 10.31949/infotech.v10i2.12083.

[4] M. Muhaemin and G. Artikel, “Analisis Pemanfaatan Artificial Intelligence (AI) sebagai Referensi dalam Desain Komunikasi Visual Analysis of Utilizing Artificial Intelligence (AI) as a Reference in Visual Communication Design Article Info ABSTRAK,” 2023. [Online]. Available: https://journal.universitasbumigora.ac.id/index.php/sasak/workflow/index/868/5❒71JournalSasak:https://journal.universitasbumigora.ac.id/index.php/sasak/index

[5] Y. A. Reza and H. Kristanto, “PERKEMBANGAN TEKNOLOGI AI DALAM DESAIN GRAFIS: SEBUAH TINJAUAN LITERATUR,” 2024.

[6] J. Li, J. Yang, J. Zhang, C. Liu, C. Wang, and T. Xu, “Attribute-conditioned Layout GAN for Automatic Graphic Design,” Sep. 2020, [Online]. Available: http://arxiv.org/abs/2009.05284

[7] C.-Y. Cheng, F. Huang, G. Li, and Y. Li, “PLay: Parametrically Conditioned Layout Generation using Latent Diffusion,” Jun. 2023, [Online]. Available: http://arxiv.org/abs/2301.11529

[8] A. D. Ramadhanti, K. R. S. Wiharja, A. Nurzakiah, and Y. Yustiawan, “Layout Generation: Automated Components Placement for Advertising Poster using Transformer-Based from Layout Graph,” Kinetik: Game Technology, Information System, Computer Network, Computing, Electronics, and Control, Aug. 2024, doi: 10.22219/kinetik.v9i4.2035.

[9] J. Lin et al., “AutoPoster: A Highly Automatic and Content-aware Design System for Advertising Poster Generation,” in MM 2023 - Proceedings of the 31st ACM International Conference on Multimedia, Association for Computing Machinery, Inc, Oct. 2023, pp. 1250–1260. doi: 10.1145/3581783.3611930.

[10] T. Yang, Y. Luo, Z. Qi, Y. Wu, Y. Shan, and C. W. Chen, “PosterLLaVa: Constructing a Unified Multi-modal Layout Generator with LLM,” Nov. 2024, [Online]. Available: http://arxiv.org/abs/2406.02884

[11] Z. Zhang, X. Zhang, J. Wei, Y. Xu, and C. You, “PosterGen: Aesthetic-Aware Paper-to-Poster Generation via Multi-Agent LLMs,” Aug. 2025, [Online]. Available: http://arxiv.org/abs/2508.17188

[12] L. Dai, Y.-H. Jiang, Y. Chen, Z. Guo, T.-Y. Liu, and X. Shao, “Agent4EDU: Advancing AI for Education with Agentic Workflows,” in Proceedings of the 2024 3rd International Conference on Artificial Intelligence and Education, New York, NY, USA: ACM, Nov. 2024, pp. 180–185. doi: 10.1145/3722237.3722268.

[13] Z. Duan and J. Wang, “Exploration of LLM Multi-Agent Application Implementation Based on LangGraph+CrewAI,” Nov. 2024, [Online]. Available: http://arxiv.org/abs/2411.18241

[14] P. Venkadesh, S. V. Divya, and K. S. Kumar, “Unlocking AI Creativity: A Multi-Agent Approach with CrewAI,” Journal of Trends in Computer Science and Smart Technology, vol. 6, no. 4, pp. 338–356, Dec. 2024, doi: 10.36548/jtcsst.2024.4.002.

[15] Deeplearning.ai, “Practical Multi-AI Agents and Advanced Use Cases with CrewAI,” Deeplearning.ai.

[16] Y. Cheng et al., “Graphic Design with Large Multimodal Model,” Apr. 2024, [Online]. Available: http://arxiv.org/abs/2404.14368

[17] R. Brioschi et al., “Sketch-to-Layout: Sketch-Guided Multimodal Layout Generation,” Oct. 2025, [Online]. Available: http://arxiv.org/abs/2510.27632

[18] Eloundou, T., Manning, S., Mishkin, P., & Rock, D. (2023). GPTs are GPTs: An early look at the labor market impact potential of large language models. arXiv. http://arxiv.org/abs/2303.10130

[19] Guo, T., et al. (2024). Large language model based multi-agents: A survey of progress and challenges. arXiv. http://arxiv.org/abs/2402.01680

[20] Bonafix, N., Frans, O., Latif CM, N., & Ardiyan. (2024). Analisis penggunaan artificial intelligence sebagai bagian dari sebuah karya visual multimedia. INFOTECH Journal, 10(2), 333–342. https://doi.org/10.31949/infotech.v10i2.12083

[21] Muhaemin, M., & Artikel, G. (2023). Analisis pemanfaatan artificial intelligence (AI) sebagai referensi dalam desain komunikasi visual. Journal Sasak. https://journal.universitasbumigora.ac.id/index.php/sasak

[22] Reza, Y. A., & Kristanto, H. (2024). Perkembangan teknologi AI dalam desain grafis: Sebuah tinjauan literatur.