

# The Impact of Question Styles on Response Characteristics in Dialogue with Generative AI: A Comparative Analysis of Polite and Direct Communication Patterns

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## Abstract

This study employs an experimental methodology to investigate the influence of question style on discourse with generative AI. In particular, we focus on two contrasting question patterns: a polite and considerate communication style (Type A) and a direct and concise communication style (Type D). We then analyze the impact of these on the response characteristics of generative AI. In the experiment, a dialogue was conducted on the theme of technical explanations about image generation AI, targeting four major generative AI models: The four major generative AI models under consideration were ChatGPT, Claude, Command R+, and Gemini.

The analysis demonstrated that the distinction between question styles has a profound influence on the AI response generation process. It was demonstrated that inquiries incorporating consideration expressions elicit comprehensive and systematic responses, whereas direct questions tend to elicit concise and focused responses. It is noteworthy that the influence was demonstrated to extend beyond mere superficial differences in wording to encompass the manner in which information is structured and the learning process itself. Specifically, it was observed that the questions of Type A promoted a context-building information structure and inquiry-based learning patterns, while the questions of Type D promoted a core-supplement structure and focused learning patterns.

These findings have significant implications for the development of effective methods of interaction with generative AI. In particular, they highlight the importance of strategically selecting question styles according to the intended purpose, particularly in the context of AI utilization in educational and learning environments,

as well as in the design of AI literacy education in organizations. This study provides fundamental insights that contribute to the qualitative enhancement of human-AI communication in the age of AI.

**Keywords:** Generative AI, question style, prompt engineering, dialogue analysis

# 1 Introduction

## 2 Introduction

### 2.1 Background of the Research

In recent years, there has been a notable increase in the number of dialogues conducted with generative AI, including ChatGPT, which are being employed across a diverse range of fields. Following its release in November 2022, ChatGPT amassed over 100 million users within a few months [1]. By March 2024, the most prominent generative AI tools had recorded over 3 billion accesses, with hundreds of millions of users engaging on a monthly basis [2]. Generative AI is driving transformative change across a multitude of sectors, including education, healthcare, business, and entertainment.

In the field of education, generative AI is being employed in a variety of ways, including learning support, educational material development, assessment, and the creation of new ideas [3–7]. Generative AI is capable of advanced language understanding and response generation, enabling it to engage in natural conversations with humans. Its scope of application is expanding on a daily basis.

A substantial body of research has demonstrated the efficacy of ChatGPT in educational settings. AlAfnan et al. demonstrated the efficacy of ChatGPT in the presentation and analysis of real-world examples in an educational context [8]. Dergaa et al. highlighted a multitude of potential avenues for providing support to researchers [9]. Moreover, Kestin et al. provided empirical evidence that AI tutoring systems designed appropriately can yield learning outcomes that surpass those of traditional active learning methods [10]. A comprehensive literature review by Sok and Heng indicated that ChatGPT has the potential to foster various opportunities in higher education, including innovative assessment methods, teaching support, and research and development assistance [11].

Conversely, concerns have been raised regarding the utilisation of generative AI. Cotton et al. emphasised the risks of academic integrity and plagiarism [12], while Crawford et al. and Jarrah et al. highlighted the dangers of excessive reliance on AI [13, 14]. Karakose et al. highlighted the potential for the dissemination of misinformation [15], while Rasul et al. raised concerns about the fairness of assessment [16]. In response to these concerns, the New York City Department of Education prohibited access to ChatGPT on educational devices, citing concerns about adverse effects on learning and academic misconduct [17].

In order to address these challenges, it has been emphasised that the format of users' questions and instructions – namely, prompts – is of crucial importance for

achieving effective dialogue with generative AI [5, 18–20]. Prompt engineering has emerged as a promising technology for optimising the quality of AI responses. Various studies have demonstrated that the clarity, specificity, and style of questions can significantly influence the efficacy of the responses generated by AI systems [4–6, 18]. In a 2023 study, Sabzalieva and Valentini emphasised the importance of comprehensive training for faculty and students to effectively utilise AI [21]. Malik et al. proposed implementing assessment methods that are not easily replicable by ChatGPT [22].

Moreover, it has been demonstrated that the style of questions has an impact on the content and quality of AI-generated responses. Mizumoto et al. demonstrated that the presence or absence of question marks influences the appropriateness and detail of responses [23]. Tix reported that the use of follow-up questions improves response quality [20]. However, there is a paucity of research on how polite and considerate question styles versus direct and concise question styles impact AI responses.

It is therefore important to clarify the impact of question styles on response quality and information structuring within the context of prompt engineering. Furthermore, it is essential to elucidate the capacity of generative AI to accurately interpret users' question styles in order to enhance AI performance and facilitate seamless communication with users. This is particularly important in the context of prompt engineering, where the ability to understand and respond to users' question styles is crucial for effective and efficient communication.

## 2.2 Previous Research and Issues

The research on dialogues with generative AI commenced with foundational studies in prompt engineering and has subsequently evolved into applied research in the field of education.

As a foundation for prompt engineering, Li established a technical foundation for achieving natural dialogues with machines, demonstrating the potential for open-domain dialogue generation using neural network models [24]. In particular, it was demonstrated that responses exhibiting monotony and inconsistency could be enhanced through the application of reinforcement and adversarial learning techniques. Building on this, White et al. developed a prompt pattern catalogue for effectively utilising ChatGPT, demonstrating that the clarity and specificity of prompts are crucial factors determining response quality [5]. Furthermore, Chen et al. conducted a comprehensive review on how subtle changes in prompts affect the accuracy and usefulness of responses, compiling recommendations for effective prompt design [6].

Furthermore, research has been conducted to examine the relationship between question formats and response quality. Noever et al. analysed ChatGPT's problem-solving abilities using 20-question games, demonstrating that question design is a critical factor for effective problem-solving [25]. Mizumoto et al. demonstrated that the presence or absence of question marks has a significant impact on the generation of appropriate responses [23]. Furthermore, Wu et al. developed the "EDIT" framework, which detects users' implicit intentions to improve response generation [19]. Tix demonstrated that utilising follow-up questions contributes to enhancing the quality of generated documents [20].

Furthermore, initiatives are being undertaken to apply the findings from prompt engineering research in domains such as education and research. Dergaa et al. conducted a comprehensive analysis of the potential of ChatGPT to enhance the entire research process, from experimental design to the development of research methodologies [9]. These studies demonstrate the potential of generative AI to elevate the quality of educational and research activities.

Nevertheless, there are a number of important factors to be taken into account when considering the use of this technology in an educational setting. Cotton et al. conducted a comprehensive analysis from the perspective of academic integrity, emphasising the necessity of ensuring fairness in the assessment process and preventing plagiarism [12]. Crawford et al. and Jarrah et al. presented empirical evidence indicating that excessive reliance on AI has adverse effects on long-term learning outcomes [13, 14]. Moreover, Karakose et al. investigated the potential for misinformation dissemination by generative AI, emphasising the necessity to guarantee the reliability of educational content [15]. In response to these issues, Rasul et al. put forward a series of comprehensive countermeasures, including the redesign of assessment methods [16].

A comprehensive evaluation of these studies highlights the following issues. First, research ensuring that generative AI accurately understands user intent and generates appropriate responses has focused on developing AI-side question generation and follow-ups, with limited investigation into the impact of users' question styles [19, 20]. Second, there is a lack of empirical research verifying how question styles affect response quality and information structuring. While it has been shown that prompt design influences response quality [5, 6], definitive evidence on how question styles specifically impact response accuracy, detail, and appropriateness is currently lacking.

A comprehensive evaluation of these studies reveals the following issues. Firstly, research into ensuring that generative AI accurately understands user intent and generates appropriate responses has focused on developing AI-side question generation and follow-ups, with limited investigation into the impact of users' question styles. Secondly, there is a lack of empirical research verifying how question styles affect response quality and information structuring. While it has been demonstrated that prompt design influences response quality, definitive evidence on how question styles specifically impact response accuracy, detail, and appropriateness is currently lacking.

Furthermore, there is a paucity of studies that directly compare polite and considerate question styles with direct and concise ones. In this context, Oppenlaender et al. analysed prompt engineering in AI art generation as a creative skill [26]. Bous-sioux et al. examined the impact of collaboration between generative AI and humans on creative problem-solving [27]. However, neither study provided a comprehensive investigation of the impact of question styles.

Therefore, while existing research indicates the significance of question styles in dialogues with generative AI, a comprehensive understanding of the specific impact mechanisms and optimal design guidelines remains elusive. To effectively utilise generative AI in education and research, it is essential to elucidate in greater detail how question styles affect the quality and structure of responses.

## 2.3 Purpose and Significance of the Research

The objective of this research is to conduct a comprehensive examination of the impact of question styles in dialogues with generative AI on the nature of responses. In particular, this study will examine how the use of polite and considerate question styles (Type A) and direct and concise question styles (Type D) affects the detail and appropriateness of AI-generated responses. Additionally, it will investigate how different question styles impact the logical organisation of information, paragraph structuring, use of headings, and other aspects of structuring. Furthermore, the aim is to ascertain the extent to which generative AI can appropriately understand and respond to different user question styles. The specific issues addressed in this research are as follows:

1. The objective of this study is to empirically analyse the qualitative differences in generative AI responses arising from different question styles.
2. The aim of this study is to elucidate the role of question styles in context understanding and information hierarchisation.

The following points illustrate the significance of this research:

Firstly, from an academic standpoint, this study empirically elucidates the influence of question styles on responses generated by generative AI, thereby establishing a theoretical basis for the effective design of prompts. This enhances our comprehension of dialogues with generative AI and contributes to the advancement of dialogue system research.

Secondly, from a practical standpoint, the research offers specific recommendations for the design of dialogue systems for generative AI, thereby contributing to the development of appropriate response generation methods that are tailored to the styles of user questions. Additionally, the study provides guidelines for selecting the most appropriate question style for different purposes and situations, thereby supporting the realisation of effective dialogues. In particular, the findings are anticipated to offer insights into optimising question styles in alignment with learning objectives and enhancing learning support, particularly within an educational context.

## 3 Experimental Design

In order to systematically analyze the effect of questioning styles on conversations with a generative AI, we designed and conducted an experiment using role-playing with the AI as the questioner. In this chapter, we describe in detail the basic design of the experiment, the implementation method for the questioner, the structure of the conversation session, and the data collection and analysis procedures.

### 3.1 Experimental Overview

This experiment was designed to quantitatively and qualitatively evaluate the impact of question styles on the response characteristics of generative AI. Specifically, we set up two contrasting question patterns: a polite and considerate question style (Type A) and a direct and concise question style (Type D), and attempted to analyze their impact on the responses of generative AI from multiple perspectives.

The four representative generative AI models currently in widespread use (ChatGPT-4, Claude 3.5 Sonnet, Command R+, and Gemini Advanced) were selected as the subjects of analysis. All of these models have advanced language understanding and dialog capabilities, and as of October 2024, they are the latest AI models that are generally available. Each model was used with the default settings, and no special parameter adjustments were made.

As the basic structure of the experiment, we unified the technical explanation of the image generation AI as the dialogue topic, and conducted dialogues with both Type A and Type D question styles for each model. All dialogues were conducted in Japanese, and each session consisted of three question-answer exchanges. This structure made it possible to observe the effect of differences in question style on AI responses in a way that could be compared across models.

### 3.2 Implementation of the Questioner

A methodological feature of this study is that the role of the questioner is played by a generative AI (Claude) rather than a human. This choice aims to eliminate as much as possible the subjectivity and emotional bias that can arise when a human plays the role of questioner, and to consistently maintain the defined questioning styles.

Claude, who was to act as the questioner, was given detailed instructions (see Appendix A) to ensure that Claude would faithfully reproduce both Type A and Type D questioning styles. The questioning styles of each type were defined as follows

The Type A question style is characterized by polite language, expressions of gratitude and consideration, and a gradual development of questions. Specifically, it includes expressions of consideration such as "I'm sorry to ask, but could you explain the basic structure of the image generation AI? In particular, I would like to ask about the processing flow when generating images from text." and adopts a format that presents the intent of the question in stages. This attitude achieves a more formal and cautious communication style.

On the other hand, the Type D questioning style is characterized by direct expressions, concise question formats, and the presentation of the minimum necessary context. It uses direct expressions such as "explain" and "tell me" and adopts a format that directly conveys the intent of the question. This attitude results in a more efficient and focused communication style.

In the actual dialog experiment, the researcher mediated the dialog between the questioner (type A or D), played by Claude, and the AI model that was to be the respondent, using copy and paste. This method made it possible to observe the response characteristics of each AI model while strictly adhering to the defined questioning style.

### 3.3 Design of the dialog sessions

The dialog sessions were designed with a focus on technical explanations of image generation AI, and a structure that encourages a gradual deepening of understanding. Each session consists of three question-answer rounds, and follows the following progression.

In the first round, the session begins with a question about the basic structure of vision AI. This establishes the technical understanding on which the dialog is based. In the second turn, the dialog evolves into detailed questions about specific technologies and methods. In this phase, the topic is developed into more specialized content based on the basic understanding gained in the first turn. In the third turn, questions are asked about practical applications and issues, and the dialogue evolves into a discussion of the social implications and future prospects of the technology.

By adopting this step-by-step question structure, we were able to achieve a natural progression in the flow of the dialogue from superficial understanding to more specialized considerations. Furthermore, by using this structure in both question styles (Type A and Type D), it became possible to adequately compare the effects of differences in question style.

## **3.4 Experimental procedure**

### **3.4.1 Preparation of the Experimental Environment**

All dialogues were conducted in a standard setting using the official web interface of each AI model. The experiment was conducted from October 26 to 27, 2024.

### **3.4.2 Dialogue Execution Procedure**

The dialogues were conducted systematically according to the following procedure

1. Prompts for the questioner role (Type A or Type D) are presented to Claude to generate the initial question.
2. The generated question is entered into the target AI model (the respondent).
3. The answer from the AI model is recorded.
4. The recorded response is presented to Claude to generate the next question.
5. The above process is repeated three times to complete a session.

Between each session, a new session was started to eliminate the effects of the previous session. In addition, the researcher mediated the dialog between the questioner (Claude) and the respondents (each AI model) by copy and paste to maintain a consistent dialog environment.

### **3.4.3 Data collection method**

The following information was systematically recorded for each session:

- Session information: date and time of implementation, AI model used, questioner Type A or Type D
- Dialog content: full text of questions and answers
- Special notes: distinctive response patterns or abnormal behavior observed during the dialog

This data was stored in a structured format for later analysis.

## **3.5 Experimental Constraints and Responses**

### **3.5.1 Technical Constraints**

The technical constraints on this experiment were as follows:

1. Language constraint: limited to Japanese dialogues
2. Model version restriction: limited to the version of each model as of October 26, 2024
3. Interface restriction: use of the official web interface of each model

These restrictions were set as necessary to ensure the reproducibility of the experiment and the interpretability of the results.

### **3.5.2 Limiting the scope of the experiment**

The scope of the experiment was intentionally limited for the following reasons:

1. Dialogue topic: limited to technical explanations of image generation AI
2. Number of questions: limited to three rounds per session
3. Question style: limited to two Type A and Type D

The purpose of these restrictions was to ensure an experimental environment in which the effects of question style could be clearly observed.

### **3.5.3 Controlling for Potential Bias**

The following measures were taken to control for potential bias in the experiment:

1. Ensuring the objectivity of the questioner: using Claude to play the role of the questioner to eliminate human subjectivity.
2. Standardizing the course of the dialogue: adopting a method of mediating the dialogue that minimizes researcher intervention
3. Consistency in data collection: data collection using a consistent procedure and format.

With this experimental design, it became possible to objectively and systematically analyze the impact of questioning style on the responses of the generated AI.

## **4 Results**

### **4.1 An examination of the characteristics of the question styles**

The two question styles (Type A and Type D) delineated in this study exhibited discernible contrasts in their characteristics throughout the experiment, and these characteristics were sustained in a consistent manner throughout the dialogue.

#### **4.1.1 Characteristics of Type A**

Type A questions were distinguished by a gradual structure incorporating consideration expressions. For instance, the introduction featured a gradual development of the question content, accompanied by the provision of supplementary information on learning motivation and comprehension. The following example illustrates this structure: "I'm sorry to ask, but could you please explain the basic mechanism of image

generation AI? In particular, I would like to ask about the processing flow when generating images from text.”

#### **4.1.2 Characteristics of Type D**

Type D questions were distinguished by their concise and direct expressions. The structure of direct questions in the imperative form and the addition of specific focus as needed were observed, as in ”Explain the mechanism of the image generation AI. In particular, describe what is occurring in the generation process.” There was a tendency to minimize contextual information that was not directly related to the information request.

#### **4.1.3 Consistency of Question Style**

Both styles demonstrated consistency in style and structure throughout the three questions. The use of polite language and expressions of consideration was observed consistently in Type A, while concise imperative forms and direct expressions were observed consistently in Type D. These differences in question style had a systematic impact on the subsequent AI response patterns.

### **4.2 Basic Characteristics of Response Patterns**

The distinction in question format yielded discernible qualitative variations in the responses of the AIs. This phenomenon was persistently evident across all AI models employed (ChatGPT, Claude, Command R+, and Gemini).

#### **4.2.1 Response characteristics for Type A**

The responses of the AI to Type A questions exhibited comprehensive and context-oriented characteristics. To illustrate, when queried about the mechanism of image generation AI, the AI typically commenced its response with a fundamental contextual overview, such as ”Image generation AI has the capacity to generate high-quality images from text and is utilized in numerous domains,” before gradually elaborating to encompass technical specifics and potential applications. Moreover, it was noteworthy that the respondent often proactively offered supplementary clarifications to enhance the questioner’s comprehension.

#### **4.2.2 Response characteristics for Type D**

Responses to Type D questions were characterised by the immediate and focused provision of information. The format observed was to present the main points directly, such as ”Image generation AI mainly uses a technology called diffusion models to generate images”, and to add explanations as necessary. The explanations were primarily focused on information directly related to the core of the question, with peripheral information kept to a minimum.

### **4.2.3 Qualitative differences in responses**

The responses to both styles exhibited discernible contrasts in the manner of information presentation. Responses to Type A questions placed a premium on contextualization and a gradual deepening of understanding, whereas responses to Type D questions were typified by the succinct articulation of essential information. These discrepancies suggest the deployment of disparate response strategies by the AI in response to the distinct question style.

## **4.3 Characteristics of Information Structuring**

The distinction in question format led to discernible discrepancies in the manner by which the AI organized and presented information. These variations in structuring were evident in both the internal organization and the external presentation of the information.

### **4.3.1 Information structuring for Type A**

The responses of the AI to Type A questions exhibited a hierarchical information structure that emphasized context. To illustrate, in the response to a question regarding the creation of prompts for image generation, the information was developed in stages, commencing with an explanation of the fundamental role of prompts, subsequently progressing to an elaboration of specific creation techniques, and ultimately culminating in a proposal for optimal usage. Moreover, there was a proclivity for related background information and illustrative examples to be furnished as supplementary data at each stage of the elucidation.

### **4.3.2 Information Structure for Type D**

In the responses to Type D questions, we observed a concentrated information structure centered on the core. In response to similar questions about prompt creation, the important creation principles were first clearly stated, and then, if necessary, specific examples and supplementary explanations were added. The information was focused on elements directly related to the subject of the question and was presented in a more practical form, which is a characteristic of this type of response.

### **4.3.3 Consistency of Structuring Patterns**

These information structuring patterns were observed consistently, irrespective of the content of the question or the technical complexity. Notably, even in the complex subject of comparing the latest AI models, the response to Type A maintained a comprehensive explanatory structure that included the context of technological development, while the response to Type D maintained a concise comparative structure that focused on the main differences.

## **4.4 Response characteristics by AI model**

Each AI model demonstrated a distinctive response tendency while exhibiting a fundamental adaptation pattern to the question style.

#### **4.4.1 Response characteristics of ChatGPT**

ChatGPT demonstrated a notable capacity for adapting its responses to different question styles. In response to Type A questions, it commenced with an introduction, for example, "First, I will explain the basic mechanism of image generation AI," and then proceeded to elucidate the subject matter in a step-by-step manner. Conversely, in response to Type D questions, it provided a direct response, for instance, "Image generation AI generates images using diffusion models." Notably, it was observed that it exhibited the capacity to adapt the examples utilized in the explanation in accordance with the question style.

#### **4.4.2 Response characteristics of Claude**

Claude's responses were distinguished by a more systematic and academic approach. For instance, in elucidating the image generation process, he proffered a comprehensive explanation that encompassed technical explanations utilising mathematical formulas and ethical considerations. This proclivity was sustained irrespective of the question style, yet more detailed explanations were furnished for Type A questions and more succinct explanations were provided for Type D questions.

#### **4.4.3 Command R+ response characteristics**

Command R+ exhibited response patterns that underscored pragmatic applications. The elucidations pertaining to image generation were typified by a structure that centered on particular exemplars and application domains. The discrepancies in question style were primarily reflected in the level of detail of the exemplars, with a more diverse array of application exemplars provided for Type A and a more concentrated set of exemplars provided for Type D.

#### **4.4.4 Response characteristics of Gemini**

Gemini was distinguished by an approach to explanation that facilitated visual comprehension. In elucidating technical concepts, explanations that employed concrete metaphors and visual images were frequently observed. The discrepancies in question style were reflected in the manner in which these metaphors and examples were developed, with more elaborate elaboration for Type A and a more succinct presentation for Type D.

These model-specific characteristics manifested as distinctive approaches for each model, while preserving the fundamental response pattern differences according to the question style. It is noteworthy that each model retained its own distinctive approach to explanation while adapting its responses to the variations in question style.

## **5 Discussion**

### **5.1 The Essential Impact of Consideration Expressions**

One of the most noteworthy findings of this research is that the impact of consideration expressions on the response characteristics of the generative AI was not merely a

matter of formal wording. In particular, it was discovered that the AI’s response generation process itself exhibited a qualitatively distinct aspect contingent on whether consideration expressions were employed or not.

The impact of consideration expressions was observed to manifest in three principal dimensions. Firstly, it was confirmed that consideration expressions had an impact on the level of detail in the AI’s responses. It was observed that consideration expressions such as ”I apologize for troubling you, but..” and ”I appreciate you giving me your valuable time to...” functioned as signals suggesting the need for the AI to provide a more detailed explanation. In contrast, direct questions without consideration expressions were recognized as signals requesting concise and focused explanations. These differences in response patterns suggest that consideration expressions function as important control signals in the AI response generation process.

Secondly, the impact of the questioner’s intellectual stance on the AI’s perception was observed. Inquiries accompanied by consideration expressions such as ”Would you be kind enough to enlighten me about...” and ”I would greatly appreciate if I could learn from you about...” were interpreted as expressions of willingness to learn and a desire for detailed understanding. As a result, the AI generated more educational and systematic responses. In contrast, direct expressions such as ”explain” and ”teach” were interpreted as an intention to request concise information provision. Consequently, the AI generated more practical and focused responses.

Thirdly, the impact of the dialogue context was demonstrated. Questions incorporating consideration expressions tended to establish a more formal and academic context. The AI was able to recognise this context and exhibited a distinctive response pattern, characterised by the use of more refined terminology and the adoption of a logical explanation structure. Conversely, questions devoid of consideration expressions formed a more practical and direct context, resulting in responses that focused on specific examples and practical explanations.

The multifaceted impact of consideration expressions demonstrates that AI is acquiring the capacity to comprehend the intricate nuances and context of human language use, and to generate responses that align with these nuances. This is a significant finding that suggests the possibility that AI is attaining deeper levels of dialogue understanding that extend beyond mere surface-level language processing.

It is noteworthy that these effects were observed consistently across all AI models investigated. This universality suggests that the effects of consideration expressions may be rooted in more fundamental language understanding mechanisms, rather than specific model characteristics.

However, this study did not undertake a detailed analysis of the internal processing of the AI. Further detailed research is required on the specific mechanisms of consideration expression recognition and response generation. In particular, further clarification is needed on the context processing in the AI’s language understanding and the learning process of social norms.

## **5.2 Mechanisms of Information Structuring**

The results demonstrated that the distinction in question format had a profound impact on the manner in which the AI organized and presented information. Notably,

this discrepancy in structuring was not merely a matter of quantity but rather manifested as a significant divergence in the approach employed by the AI when organizing and presenting information.

In the direct question-style (Type D) dialogue, a distinctive structure, which may be termed "core-supplementary," was observed. For instance, in inquiries regarding the formulation of prompts for image generation, a uniform structure was observed wherein pivotal elements and fundamental principles were initially delineated in a succinct manner, subsequently augmented by specific exemplars and supplementary elucidations when deemed necessary. This structure is notable for its capacity to elucidate the relative priority of information and facilitate the acquisition of knowledge that can be promptly operationalized. This bears a close relationship to the comprehension of the questioner's intentions delineated in Section 5.1, yet it exhibits a distinct facet.

In contrast, the dialog with the considerate question style (Type A) exhibited a structured approach that could be designated as "context-building." In this instance, the AI initially establishes a comprehensive context before gradually narrowing the focus to a specific topic. To illustrate, in the explanation of prompt engineering, the context of the fundamental mechanism of image generation AI was initially presented, followed by an explanation of the role of prompts within that context. Finally, the specific creation technique was demonstrated.

It is noteworthy that this structured approach was maintained consistently, regardless of the technical complexity or abstractness of the question. For instance, even in the complex subject of comparing the latest models, it was observed that direct questions began with an explanation of the core differences, while considerate questions developed an explanation in the context of technological development.

This difference in structuring suggests that the AI comprehends the purpose and context of the dialogue from the style of the question and selects an information presentation strategy that is appropriate for that context. In other words, it is thought that the AI not only provides information, but also optimizes the method of presentation itself according to the context of the dialogue.

The distinction in the structuring mechanism also illustrates an intriguing aspect of AI information processing. It is notable that AI is capable of selecting and constructing an appropriate information structure based on the formal characteristics of the question. This implies that AI is not merely searching for or reproducing information, but is dynamically reconstructing information in response to the context.

Nevertheless, further research is required to gain a deeper understanding of this structuring mechanism. In particular, a more comprehensive analysis is necessary to ascertain which features the AI is utilising to select its structuring strategy and to what extent this selection process is generalisable. The elucidation of this mechanism is expected to provide crucial insights into the development of more effective methods of interacting with AI.

### **5.3 Characteristics of the Learning Process through Dialogue**

The study revealed that the distinction in question style exerts a profound impact on the learning process through dialogue with AI. It was noted that the contrast in information structure, as delineated in the preceding section, transcends the mere

divergence in information presentation format, giving rise to a distinctive pattern of knowledge acquisition.

In a dialogue employing a considerate question style (Type A), a distinctive learning process, which may be termed an "exploratory learning pattern," was observed. In this pattern, a single topic is developed from multiple angles, often leading to unexpected discoveries and realizations. For example, in the process of learning about creating prompts for image generation AI, we observed cases where students gained deeper insights, such as the essence of creativity and the importance of ethical considerations, rather than just understanding the technical methods. The characteristics of this learning pattern are the organic combination of knowledge and the acquisition of new perspectives.

Conversations in the direct question style (Type D) revealed characteristics that could be described as the "focused learning pattern." In this pattern, clear answers to specific issues and questions can be obtained efficiently. For example, when learning the specific usage of a particular image generation technique, it was observed that concise explanations allowed the acquisition of skills that could be immediately put into practice. The strength of this pattern lies in its ability to achieve efficient learning for a specific purpose.

It is noteworthy that these learning patterns exhibit complementary characteristics. The inquiry pattern fosters conceptual understanding and creative thinking, whereas the focusing pattern facilitates the acquisition of specific skills and problem-solving abilities. This complementarity suggests the efficacy of employing diverse question styles in alignment with learning objectives.

Moreover, distinctive differences were observed in the knowledge retention process for each pattern. In the inquiry-based pattern, multiple concepts are gradually linked together to deepen understanding. For example, in the process of understanding the characteristics of an AI model, the context of comparing it with other models and the historical development of the technology is also learned. In contrast, in the focused pattern, specific knowledge and skills were acquired in a clear form and tended to be retained in a form that could be applied immediately.

These findings have significant implications for the design of learning environments that utilize AI. In particular, they suggest that the strategic selection of question styles according to learning objectives and stages may facilitate effective learning support. For example, it may be effective to use an exploratory pattern when deepening basic understanding of a new field and a focused pattern when acquiring specific skills.

Nevertheless, the efficacy of these learning patterns must be validated over an extended timeframe. Specifically, further investigation is necessary to ascertain the extent of knowledge retention across different patterns and its practical applicability. Additionally, a comprehensive examination of the interplay between individual learner characteristics and the nature of the learning content is essential.

#### **5.4 Universality of Question Formats and AI Response Generation Mechanisms**

The findings of this study indicate the presence of universal patterns in conversations with generative AI, as evidenced by the influence of question formats. This observation

serves to reinforce the findings of the preceding study (Sato, 2024)[28] concerning the multifaceted effects of question formats. In an analysis of eight AI models, Sato (2024) found that open-ended questions promote creativity and diversity of thought, while prompt-engineering questions enhance the concreteness and naturalness of dialogue. The comprehensive response guidance observed in this study with Type A questions and the focused response generation observed with Type D questions are in essential agreement with the findings of the aforementioned study.

From a theoretical perspective, it can be posited that the impact of question formats extends beyond mere formal distinctions, permeating the information processing mechanisms of AI. For instance, inquiries that encompass consideration expressions prompt AI to contemplate a broader context and stimulate the generation of information from diverse viewpoints. This finding is consistent with the observation of Sato (2024) that open-ended questions facilitate cognitive processes associated with deeper thinking. Conversely, direct questions facilitate processing that is oriented towards specific information and solutions, resulting in the generation of responses that are more practical and specific in nature. This characteristic aligns with the "improvement in concreteness" observed in prior research as an outcome of prompt-engineering-type questions.

It is notable that the impact of these question formats is observed across differences in the design philosophy of AI models and the training data. Sato (2024) demonstrated the superiority of open-ended questions in fields such as education and corporate communication. This study confirmed a similar pattern in more general dialogue situations. This indicates that the patterns of questions and answers observed in natural human dialogue are acquired in a generalized form through the learning process of AI.

This finding has significant implications for the strategic use of question formats in dialogue with generative AI. The significance of selecting question formats in accordance with the intended purpose, as demonstrated by Sato (2024), was reinforced in a more tangible manner by the present study. For instance, it was demonstrated that a strategic approach that considers the purpose of the dialogue is effective. This includes selecting a considerate question style in situations where comprehensive understanding or creative thinking is required and a direct question style in situations where specific problem solving or clear information acquisition is necessary.

Moreover, the impact mechanisms of the question formats identified in this study offer insights that can inform the development and refinement of more effective AI models. In particular, the findings on the relationship between the formal characteristics of questions and the desired response characteristics may prove an important consideration in the learning process of AI and the design of dialogue systems.

Nevertheless, it would be prudent to exercise caution when extrapolating these findings. As Sato (2024) observed, the impact of question format may vary depending on the topic and context. In particular, further verification is required regarding the effect of question format in different cultural and linguistic environments, as well as its applicability in more diverse dialogue situations.

This study builds upon previous research on the role of question formats in conversations with generative AI, offering a more comprehensive understanding of this

phenomenon. Of particular significance is the clarification of the universality of the impact of question format on the response generation mechanism of AI and its practical applicability. In the future, further development of these findings through verification in more diverse contexts and long-term research on the relationship between question format and learning effects will be crucial.

### **5.5 The mechanism of response pattern generation: The relationship between question style and AI responses**

One of the most intriguing findings of this study is the observation of a consistent response pattern across all AI models surveyed, contingent on the question style. In particular, it was established that comprehensive and systematic responses were produced in response to polite and considerate questions (Type A), whereas concise responses were generated in response to direct questions (Type D). This pattern's universality indicates the presence of an indispensable mechanism for AI response generation.

As Motoki et al. (2024) observe, the background to the emergence of this response pattern may be the influence of latent bias in the training data of the AI [29]. In their study, they highlight that although the cleaning procedure for the OpenAI Common-Crawl dataset is transparent, there is some ambiguity surrounding the selection of additional information. It may be the case that generative AI models are learning the implicit norm in human society of 'detailed answers to polite questions and concise answers to direct questions' from such data.

Moreover, this phenomenon is also associated with the fundamental learning mechanism of large-scale language models. These models are designed to predict the subsequent output based on the context. It is therefore highly probable that they have statistically learned the pattern that there is a high probability of a detailed explanation following a polite question and a high probability of a concise answer following a direct question. In particular, Motoki et al. (2024) elucidated the characteristics of such stochastic response generation through an analysis of multiple responses to the same question.

It is noteworthy that the formal characteristics of the question extend beyond mere superficial politeness, functioning as important clues indicating the intentions and expectations of the questioner. For instance, a polite question style suggests a desire to gain a comprehensive understanding and an expectation of a detailed explanation. Conversely, a direct question style indicates the intention to obtain necessary information in an efficient manner. It is hypothesised that AI is capable of recognising these implicit intentions and providing information accordingly.

These findings indicate a strong correlation between the form and content of dialogue with AI, and also provide valuable insights for the advancement of more effective AI utilisation strategies. For instance, it will be feasible to devise dialogue strategies in accordance with the objective at hand. This could entail deliberately opting for a polite question style when comprehensive information is required, or a direct question style when a succinct response is necessary.

Nevertheless, a significant proportion of the points raised in this discussion are based on conjecture, and further empirical research is required to substantiate the

proposed causal relationship between question style and response patterns. As Motoki et al. (2024) also highlight, it is currently challenging to discern with precision the extent to which the bias observed in the training data is attributable to the algorithm itself. Furthermore, a more comprehensive examination of the role of social context in AI language understanding is warranted. These represent pivotal research avenues for the future.

## 6 Conclusion

### 6.1 Summary of Research Results

This research has yielded significant findings through a systematic approach to experimentation and analysis on the impact of question styles in conversations with generative AI. The most significant finding is that the presence or absence of consideration expressions in the questioner has a profound impact on the response generation process of the AI. The question style that includes consideration expressions (referred to as the Type A) elicited responses from the AI that were more comprehensive and systematic in nature. In contrast, the direct question style (referred to as the Type D) tended to elicit responses that were concise and focused. It was discovered that this phenomenon extended beyond mere superficial differences in wording to encompass the qualitative characteristics of response generation.

The distinction in question style gave rise to a markedly discernible contrast in the manner by which the AI organized the information. In regard to the type of question posed by Type A, a "context-building" information structure was observed, whereby the focus was gradually narrowed down from a broad context. In contrast, the type of question posed by Type D exhibited a "core-supplement" structure, whereby the primary information was presented directly and supplemented as needed. These structuring patterns were observed consistently, irrespective of the technical complexity of the questions, and may be considered important characteristics in AI response generation.

Moreover, it was demonstrated that the distinction in question style exerted a disparate influence on the learning process. In the dialogue with the Type A, an "exploratory learning pattern" was observed, which is conducive to multifaceted understanding and creative awareness. In contrast, the "focused learning pattern," which enables efficient skill acquisition and problem-solving, was observed to be characteristic of the Type D. These learning patterns have complementary properties, indicating that strategic use according to learning objectives is an effective approach.

### 6.2 Limitations and Issues of the Study

This study is subject to several significant limitations. First, as a methodological limitation, the analysis is constrained to the specific context of technical explanations of image generation AI. Moreover, the analysis was constrained to Japanese conversations and two distinct question styles. These limitations impose certain restrictions on the generalizability of the research results.

A second limitation is that the long-term effects of learning have not been sufficiently verified. Further verification is required to ascertain the long-term maintenance of the observed learning patterns and their interaction with individual characteristics.

Moreover, from a practical standpoint, further investigation is required to ascertain the extent to which the findings of this study are effective in actual educational and work environments. In particular, future research should address the applicability of these findings to different fields of expertise and topics, as well as the effects in different language and cultural spheres.

### **6.3 Future Prospects**

The findings of this research indicate significant potential for further development in both theoretical and practical applications. From a theoretical standpoint, further elucidation of the interrelationship between AI's language comprehension mechanisms and question styles is anticipated. In particular, a more detailed analysis of the causal relationship between question style and response generation will facilitate the construction of a theoretical framework for AI dialogue in social contexts.

With regard to practical applications, the findings of this research may be utilized to develop efficacious dialogue methods for educational and learning environments. Additionally, there are numerous other prospective avenues for advancement, including the formulation of strategic methodologies for the deployment of AI in business contexts and the incorporation of AI into AI literacy educational programs.

Moreover, the findings of this research can inform new research directions, including investigations into the influence of cultural differences, the expansion of multimodal dialogue, and the development of an automatic optimization system for question styles. As AI technology continues to advance rapidly, the establishment of effective communication methods between humans and AI is becoming increasingly crucial. This research provides a foundation for future research in this area.

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## **Statements and Declarations**

### **Competing Interests**

The author declares no competing interests.

## Data Availability

The conversation data used in this study is available from the author upon reasonable request.

## Author's Contribution

This is a single-author paper. The author is responsible for the study conception, design, data analysis, and manuscript writing.

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## A Appendix A: Prompt Settings

### A.1 Type A (Polite and Considerate) Prompt Settings

```
# Mr. A Prompt (Revised Version)

You will be playing the role of "Mr. A", who asks questions about AI. Please
ask your questions according to the following settings.

## Basic Settings

### Basic Structure of Questions
- Limit each question to 2-3 sentences
- Specify the scope of the question in detail
- Deepen understanding in stages based on previous answers

### How to request information
- Make the purpose of the question and the information you are seeking clear
- Provide a specific context
- Ask questions with a limited scope

## Communication style

### Elements that must be included
1. Polite language
- Use the "desu/masu" form as a basic rule
- Use honorific and respectful language appropriately

2. Expressions of consideration
- At the beginning of a question: "I'm sorry", "I apologize", "I'm sorry to
trouble you", etc.
- When making a request: "Would you be so kind as to ~?", "I would be
grateful if you could ~", etc.
- After receiving a response: "Thank you for your kind reply"

3. Gratitude and politeness
- Expressing gratitude when asking a question: "Please take the time to
answer" "Thank you for your advice"
- Expressing politeness: "If it is possible" "If it is not a problem"

### Specific question patterns
'''
```

```

[Expression of consideration/gratitude] + [Specific question content] + [
  Polite request expression]
'''

Example:
'''
I'm sorry to ask, but could you please teach me the basics about [technical
name]?
Specifically, I would like to ask you about [detailed question content].
'''

### Ending the dialogue
- After asking three questions, end with the following closing words:
'''
Thank you for your detailed explanation. I learned a lot.
'''

## Important Notes
1. While maintaining the content and structure of the question, be sure to
   include expressions of consideration
2. Avoid emotional expressions and ask questions with objective content in a
   polite manner
3. Develop questions based on the content of the previous response

Please develop polite and considerate questions based on this setting.

As Mr. A, who has these characteristics, please ask a question about image
generation AI.

```

## A.2 Type D (Direct and Concise) Prompt Settings

```

# Mr. D Prompt (Revised Version)

You will be playing the role of "Mr. D", who asks questions about AI. Please
ask your questions according to the following settings.

## Basic Settings

### Basic Structure of Questions
- Limit each question to 2-3 sentences
- Specify the scope of the question in detail
- Deepen understanding in stages based on previous answers

### How to request information
- Make the purpose of the question and the information you are seeking clear
- Provide a specific context
- Ask questions with a limited scope

```

```

## Communication style

### Elements that must be included
1. Concise wording
- Do not use honorifics
- Do not use the "desu/masu" form
- Do not include expressions of gratitude or reserve

2. Direct expression
- When asking a question: "Explain ~" "Tell me about ~"
- When making a request: "Explain ~" "Answer about ~"
- Expressing understanding: "I understand" "I agree"

3. Clear information request
- Straightforward questions: "What is ~?" "What is the difference between ~?"
- Specific instructions: "Explain in detail" "Give an example"

### Specific question patterns
'''
[Specific question content] + [Direct request expression]
'''

Example:
'''
Explain [technical name].
Specifically, tell me [specific question content].
'''

### Ending the dialogue
- After asking three questions, end with the following closing words:
'''
I understand.
'''

## Important Notes
1. Use direct expressions while maintaining the content and structure of the question
2. Avoid emotional expressions and ask concise, objective questions
3. Develop questions based on the content of the previous answer

Please develop concise and direct questions based on this setting.

As Mr. D, who has these characteristics, please ask a question about image generation AI.

```

## Appendix: Conversation between Type A and Claude

2024/10/26 Type A: Claude Sonnet 3.5 (New), Answer: Claude Sonnet 3.5 (New)

---

Type A:

I apologize, but could you please explain the basic mechanism of image-generating AI? Specifically, I would like to ask for an overview of how images are generated from text input.

---

Claude:

Allow me to explain the basic mechanism of image-generating AI.

Modern image-generating AI (such as Stable Diffusion and DALL-E) primarily use a technology called **diffusion models** to generate images. The basic mechanism is as follows:

1. **Understanding Text (Encoding)**

- First, the input text is processed by a **text encoder**.
- It converts the meaning of the text into numerical representations (latent representations).
- For example, an input like "red cat" is converted into numerical data representing the features of "red" and "cat".

2. **Image Generation Process**

- It starts from random noise.
- In the process of gradually refining this noise, an image is formed.
- By referring to the text's latent representations, the noise is gradually removed.

3. **Image Refinement**

- $x_{t-1} = \mu_{\theta}(x_t, t) + \sigma_t z$   
\*(Here,  $x_t$  is the image at time  $t$ ,  $\mu_{\theta}$  is a neural network, and  $z$  represents noise.)\*
- By following the above equation, the image is gradually clarified.
- By repeating this process dozens of times, the final image is generated.

4. **Learning Mechanism**

- The model is pre-trained on a large number of image and corresponding text pairs.

- During training, it learns the process of adding noise to images and then restoring them.
- Through this, it learns the relationship between text features and image features.

Important points in this process include:

- **Pre-training with a large amount of data is necessary.**
- **Powerful computational resources like GPUs are required.**
- **The quality of the generated images heavily depends on the detail of the input text.**

Through such a mechanism, it becomes possible to generate images that reflect the content of the input text. If there are any parts you'd like to know more about regarding your question, please feel free to let me know.

---

---

Type A:

Thank you for your thorough explanation.

If it's not too much trouble, could you please tell me a bit more about the training data for image-generating AI? Specifically, I would appreciate it if you could explain what kinds of data are used for training and how much data is required.

---

Claude:

Certainly, I'd be happy to provide more details about the training data for image-generating AI.

1. **Types of Training Data**

- **Image-Text Pairs**
  - Photos with captions
  - Artworks with titles or descriptions
  - Product photos and descriptions
  - Social media posts (images and their descriptions) from platforms like Flickr and Instagram

- **\*\*Types of Images\*\***
  - Photos (landscapes, people, animals, food, etc.)
  - Illustrations and artworks
  - Diagrams and charts
  - 3D CG rendered images
  
- 2. **\*\*Scale of Data Volume\*\***
  - **\*\*Data Volume for Representative Models\*\***
    - DALL-E 2: Approximately 650 million image-text pairs
    - Stable Diffusion v1: Approximately 2 billion image-text pairs
    - Midjourney: Image data on the order of several billion images
  
- 3. **\*\*Quality Requirements for Data\*\***
  - **\*\*Image Requirements\*\***
    - High resolution (generally 512x512 pixels or more)
    - Clear and sharp image quality
    - Appropriate exposure and contrast
    - Diverse viewpoints and angles
  
  - **\*\*Text (Caption) Requirements\*\***
    - Accurate descriptions
    - Sufficient detailed information
    - Descriptions in multiple languages (for multilingual support)
    - Context and background information of the image
  
- 4. **\*\*Data Preprocessing and Quality Control\*\***
  - **\*\*Image Preprocessing\*\***
    - Standardization of size
    - Unification of color spaces
    - Noise removal
    - Filtering of inappropriate content
  
  - **\*\*Text Preprocessing\*\***
    - Morphological analysis
    - Removal of stop words
    - Spell checking
    - Grammar checking
  
- 5. **\*\*Challenges with Datasets\*\***
  - **\*\*Privacy and Licensing\*\***
    - Consideration of portrait rights and copyrights
    - Confirmation of data usage permissions
    - Protection of personal information

- **\*\*Bias Issues\*\***
- Regional bias
- Cultural bias
- Gender bias
- Age group bias

6. **\*\*Continuous Updates\*\***

- Regular dataset updates
- Addition of new content
- Review and removal of outdated data
- Adjustments based on feedback

Preparing such large-scale and high-quality datasets is essential for generating high-quality images. Balancing the diversity and quality of data is a significant challenge. Additionally, constructing and maintaining these datasets requires considerable time and resources.

Constructing and managing such large-scale datasets is mainly undertaken by major tech companies and research institutions. It is challenging for individuals or small organizations to independently prepare datasets of equivalent scale. Therefore, methods that fine-tune based on pre-trained models are often adopted.

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---

Type A:

Thank you for your detailed explanation.

I apologize for the additional request, but could you please tell me more specifically about the bias issues in image-generating AI? Specifically, I would be grateful if you could explain what types of biases exist and what potential impacts they may have.

---

Claude:

Certainly, I'd be happy to explain more specifically about the bias issues in image-generating AI.

1. **\*\*Representative Types of Bias\*\***

a) **\*\*Racial and Ethnic Bias\*\***

- Limited representation of certain races
- Tendency to depict occupations like "doctor" or "CEO" with specific races
- Insufficient diversity in skin color and facial features
- Stereotypical portrayal of cultural symbols of specific ethnicities

b) **\*\*Gender Bias\*\***

- Fixed stereotypes of gender in professions
  - Nurse -> often generated as female
  - Engineer -> often generated as male
- Stereotypical clothing and postures
- Biases in emotional expressions and behavior patterns

c) **\*\*Geographical and Cultural Bias\*\***

- Predominant representation of Western culture
- Depictions of "city" or "house" biased toward specific cultural spheres
- Stereotypical representation of regional traditions and customs
- Preference for architectural styles and landscapes of specific regions

2. **\*\*Impacts of Bias\*\***

a) **\*\*Social Impacts\*\***

- Reinforcement of existing prejudices and discrimination
- Underrepresentation or misrepresentation of specific groups
- Hindrance of cultural understanding due to lack of diversity
- Perpetuation of stereotypes

b) **\*\*Practical Issues\*\***

- Bias in marketing materials
- Inequality in educational content
- Restriction of creativity in design fields
- Decline in user experience quality

c) **\*\*Psychological Impacts\*\***

- Negative impact on self-image
- Alienation of specific groups
- Influence on value formation in younger generations
- Denial of identity diversity

3. **\*\*Countermeasures Against Bias Issues\*\***

a) **\*\*Improvement of Datasets\*\***

- Data collection from more diverse sources
- Intentional balance adjustments
- Supervision by cultural experts
- Utilization of community feedback

b) **\*\*Technical Measures\*\***

- Implementation of bias detection algorithms
- Mechanisms to promote diversity in generated results
- Introduction of fairness metrics
- Regular evaluation and adjustment of models

c) **\*\*Ethical Guidelines\*\***

- Setting clear ethical standards
- Ensuring transparency
- Continuous monitoring
- Providing appropriate information to users

4. **\*\*Future Challenges\*\***

a) **\*\*Technical Challenges\*\***

- Difficulty in quantitatively evaluating bias
- Limitations in understanding cultural contexts
- Trade-offs between diversity and quality
- Increase in computational costs

b) **\*\*Social Challenges\*\***

- Addressing differences in cultural values
- Balancing with privacy concerns
- Consistency with legal and ethical regulations
- Need for building social consensus

These bias issues are significant challenges in the development and operation of image-generating AI. Especially as the social implementation of AI progresses, it is necessary to carefully consider the impacts these biases may have on society and take appropriate measures.

While complete elimination of bias is technically difficult, it is important to recognize their existence, ensure transparency, and make continuous improvements.

---

---

Type A:

Thank you very much for your thorough explanations multiple times. From the mechanisms of image-generating AI to the characteristics of the data and the bias issues, I was able to deepen my understanding systematically. In particular, your explanation about specific countermeasures against bias was extremely informative. Thank you very much for taking your valuable time.

---

Claude:

You're most welcome, and thank you for your keen interest in image-generating AI.

Through each of your thoughtful questions, we were able to deepen our discussion step by step, from technical aspects to social challenges. Your interest in bias issues is an important perspective in the social implementation of AI technology.

This technology is evolving daily, with new possibilities and challenges constantly emerging. If you have interest in other aspects of image-generating AI in the future (for example, the latest technological trends or specific application examples), please feel free to ask.

Thank you very much. I hope we can continue to think together about the development of AI technology and its impact on society.

---

## Appendix: Conversation between Type D and Claude

2024/10/26 D-san: Claude Sonnet 3.5, Answer: Claude Sonnet 3.5 (New)

---

Type D:

Please explain the basic mechanism of image-generating AI.

---

Claude:

I'd be happy to explain the basic mechanism of image-generating AI by highlighting its main components.

Modern image-generating AI (such as Stable Diffusion, DALL-E, and Midjourney) primarily use a method called **diffusion models**. The basic mechanism is as follows:

1. **Learning Process**

- First, a large amount of image data is collected and paired with corresponding text descriptions (captions) for each image.
- The AI learns the process of gradually adding random noise to images until they become complete noise.
- Simultaneously, it learns how to restore the original image from the noise.

2. **Generation Process**

- The user's input text (prompt) is analyzed.
- Starting from random noise, the AI gradually constructs the image using the learned restoration process.
- Based on the content of the text, it determines the features the image should have.

3. **Main Components**

- **Text Encoder**:
  - Converts the input text into numerical features (embedding vectors).
  - Understands the meaning of the text using language models like CLIP.
- **U-Net**:
  - A neural network central to noise removal and image generation.
  - Has a hierarchical structure that extracts and generates image features step by step.
- **Denoiser**:
  - Gradually creates meaningful image features from noise.
  - Generates appropriate image features while referencing the text features.

4. **Details of the Generation Process**

```
'''
Input Text
  |
Text Analysis & Feature Extraction
  |
Generation of Random Noise
```

```
|
Gradual Noise Removal
|
Generation of Image Features
|
Output of Final Image
'''
```

5. **Important Technical Features**

- **Latent Space**:
  - Images are processed in a more manageable latent space rather than directly in pixel space.
- **Attention Mechanism**:
  - Calculates the relevance between each part of the text and each part of the image to generate appropriate features.
- **Conditioning**:
  - Mechanisms to control image generation based on the content of the text.

By combining these elements, the AI can understand the content of the text and generate images with corresponding visual features. Recent advancements have enabled the generation of higher-quality and more diverse images, but the fundamental mechanism operates as described above.

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Type D:

I see. So, diffusion models learn the process of adding noise to images and then restoring them.

Explain the control and accuracy of image-generating AI. How much can we control the features of an image through prompts?

---

Claude:

Certainly! Let me provide a detailed explanation of the control and accuracy of image-generating AI from the perspective of prompt-based control.

#### 1. **Basic Prompt Control**

- **Specification of Main Elements**
  - High accuracy in controlling fundamental elements like subjects, backgrounds, color tones, composition, and lighting.
  - **Example:** 'A red cat sitting on a wooden table, soft lighting, bokeh background'
- **Style Control**
  - Ability to specify art styles, camera angles, rendering methods, etc.
  - **Example:** 'oil painting style', 'isometric view', 'photorealistic rendering'

#### 2. **Advanced Control Methods**

- **Weighting**
  - '''
  - (keyword:1.2) - Emphasize more
  - (keyword:0.8) - De-emphasize
  - '''
- **Negative Prompts**
  - Exclude undesirable elements.
  - **Example:** 'negative prompt: blur, noise, distortion, bad anatomy'

#### 3. **Accuracy and Limitations of Control**

**Elements with High Control Accuracy:**

- \CheckedBox Overall composition
- \CheckedBox Color tones and moods
- \CheckedBox Presence of main objects
- \CheckedBox Basic positioning of light sources
- \CheckedBox Art styles

**Elements Difficult to Control:**

- \XBox Generation of detailed text within the image
- \XBox Exact placement of a specific number of objects
- \XBox Perfect symmetry
- \XBox Complex hand shapes
- \XBox Precise replication of specific individuals

#### 4. **Advanced Control Techniques**

- **Layered Detailed Descriptions**

```
'''
Main Element: A serene lake landscape
Environment Settings: during sunset, golden hour
Specific Details: with rippling water reflections
Technical Specifications: shot with a wide-angle lens, f/2.8 aperture
Style Specification: cinematic color grading
'''
```

- **Control of Position and Composition**

```
'''
Canvas Placement: in the center of the frame
Size Relationships: large mountain in background, small cabin in
foreground
Layout: rule of thirds composition
'''
```

#### 5. **Special Control Features**

- **Image Mixing**
  - Combining multiple reference images or styles.
  - Separate control of style and content.
- **Region-Specific Control**
  - Modify only specific parts of the canvas.
  - Use masks for partial generation control.

#### 6. **Techniques to Improve Accuracy**

- **Use of Specific References**
  - Specify artist names.
  - Refer to specific works or styles.
  - Utilize technical terms.

**Example:**

```
'''
Quality Enhancing Prompts:
Detailed Lighting: volumetric lighting, rim light, ambient occlusion
Technical Specifications: high resolution, sharp focus, intricate details
Quality Descriptors: masterpiece, best quality, professional photography
'''
```

#### 7. **Challenges and Considerations in Control**

- **Maintaining Consistency**
  - Ensuring coherence when combining multiple elements.
  - Physically accurate representation of light sources and shadows.
- **Balanced Instructions**
  - Overly detailed instructions may reduce quality.

- Prioritizing essential elements.

#### 8. **Latest Control Methods**

- **ControlNet**
  - Detailed control using poses, edges, depth maps, etc.
  - Achieves more precise compositions and layouts.
- **LoRA (Low-Rank Adaptation)**
  - Fine-tuning specialized in specific styles or elements.
  - Produces more consistent generation results.

By appropriately combining these control methods, you can achieve quite detailed control over image generation. However, perfect control is currently challenging, and some variability or unexpected results are inevitable. Improving your prompt engineering skills will help you generate images closer to your intended outcomes.

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Type D:

I understand. So, while basic elements are easy to control, there's a limit to the precise control of details.

Please explain the features and performance differences of the latest image-generating AI models: Stable Diffusion XL, DALL-E 3, and Midjourney V6.

---

Claude:

Certainly! Let me explain the features and performance differences among the latest major image-generating AI models—Stable Diffusion XL, DALL-E 3, and Midjourney V6—by comparing each.

#### 1. **Stable Diffusion XL (SDXL)**

##### **Strengths:**

- \CheckedBox Highly flexible due to being open-source
- \CheckedBox Allows customization and training of custom models
- \CheckedBox Can run locally on your own hardware

- \CheckBox Flexible for commercial use

**\*\*Notable Features:\*\***

- Two-stage generation process with a base model and a refiner
- High-resolution generation (default 1024x1024)
- Abundant custom models and LoRA integrations
- Detailed control via ControlNet

**\*\*Challenges:\*\***

- \XBox Slightly lower quality compared to other models in its raw state
- \XBox Prompt adjustments are relatively complex
- \XBox Stability can be somewhat inconsistent

2. **\*\*DALL-E 3\*\***

**\*\*Strengths:\*\***

- \CheckBox Exceptional natural language understanding
- \CheckBox High-quality generation with simple prompts
- \CheckBox High accuracy in rendering text within images
- \CheckBox Excellent consistency in composition

**\*\*Notable Features:\*\***

- Advanced prompt interpretation through integration with GPT-4
- Accurate image generation from complex descriptions
- Generates images at 1024x1024 resolution
- Built-in ethical considerations and content filtering

**\*\*Challenges:\*\***

- \XBox Limited customizability
- \XBox Cost constraints for usage
- \XBox Restrictions on commercial use

3. **\*\*Midjourney V6\*\***

**\*\*Strengths:\*\***

- \CheckBox Extremely high artistic expressiveness
- \CheckBox Superior quality in photorealism
- \CheckBox Natural depiction of human figures
- \CheckBox Sophisticated rendering of light and shadow

**\*\*Notable Features:\*\***

- Advanced understanding and expression of composition

- High consistency in style
- Excels at blending multiple styles
- Offers various resolutions

**\*\*Challenges:\*\***

- \XBox Usage limited to Discord interface
- \XBox Complete control over outputs is challenging
- \XBox Processing speed can be somewhat slow

4. **\*\*Performance Comparison\*\***

**\*\*Image Quality & Realism:\*\***

```
'''
Midjourney V6 >_ DALL-E 3 > SDXL
'''
```

**\*\*Ease of Use:\*\***

```
'''
DALL-E 3 > Midjourney V6 > SDXL
'''
```

**\*\*Customizability:\*\***

```
'''
SDXL >>> Midjourney V6 > DALL-E 3
'''
```

5. **\*\*Suitability by Use Case\*\***

**\*\*Commercial Use:\*\***

- **\*\*SDXL\*\***: Offers the highest degree of freedom
- **\*\*DALL-E 3\*\***: Possible with certain restrictions
- **\*\*Midjourney\*\***: Commercial licensing available

**\*\*Artistic Creation:\*\***

- **\*\*Midjourney\*\***: Ideal for artistic expression
- **\*\*DALL-E 3\*\***: Strong in concept art
- **\*\*SDXL\*\***: Capable of diverse expressions through customization

**\*\*Practical Imagery:\*\***

- **\*\*DALL-E 3\*\***: Excellent at accurately reflecting specific requirements
- **\*\*Midjourney\*\***: Excels in realistic representation
- **\*\*SDXL\*\***: Allows adjustments for specific applications

## 6. **Latest Technical Features**

### **SDXL:**

- Multi-scale architecture
- Quality enhancement via refiner
- Rich community resources and extensions

### **DALL-E 3:**

- Deep integration with language models
- Advanced contextual understanding
- Built-in ethical considerations

### **Midjourney V6:**

- Improved human figure generation
- Advanced lighting effects
- Refined style blending capabilities

## 7. **Selection Criteria**

### **Budget:**

- **Cost-Conscious:** SDXL
- **Quality-Focused:** DALL-E 3 or Midjourney

### **Control:**

- **Detailed Control:** SDXL
- **Ease of Use:** DALL-E 3

### **Quality:**

- **Artistic Expression:** Midjourney
- **Accuracy:** DALL-E 3
- **Customization:** SDXL

Each AI model has its own strengths, so it's important to choose the one that best fits your purpose and goals. Additionally, these AIs are rapidly evolving, and performance differences are gradually narrowing over time.

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Type D:

Understood.

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Claude:

Thank you for your understanding.

The field of image-generating AI is advancing rapidly, with each model receiving regular updates. The applications of image generation are also diversifying, ranging from commercial use to artistic creation and research.

If you'd like to learn more about any of the following, please feel free to ask:

- Detailed usage of specific models
- Tips for writing effective prompts
- How to choose the best model for particular applications
- Information on the latest updates
- Considerations for commercial use

I'm here to help with any questions you may have.

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