The Unasked Questions in AI

(AIGuide 6)

A Structured Examination of How AI Is Used—and What Remains Unexplored

AI Sourced Facts (AISF) Pte. Ltd.

Edition: Version 1.0
Publication Date: April 2026

Preface

This Guide forms part of the AISF AI Guidance Series, developed to support structured understanding of how artificial intelligence systems are engaged in practice.

While much of the public discourse around AI focuses on capabilities, tools, and outputs, this Guide adopts a different perspective. It examines patterns of interaction—specifically, what is consistently *not* asked when individuals and organisations engage with AI systems.

The observations presented here are not derived from a single system or viewpoint. They reflect a cross-system perspective, informed by interactions across multiple globally deployed AI systems. This approach aligns with AISF's commitment to neutrality, non-endorsement, and structured reasoning.

This Guide does not seek to instruct, optimise, or prescribe how AI should be used. Instead, it aims to provide a clear and structured lens through which current patterns of AI use can be understood.

Introduction — Purpose of This Guide

The purpose of this Guide is to examine a dimension of AI use that is often overlooked: the absence of certain types of questions.

Most analyses of AI interaction focus on what users ask—how prompts are constructed, what outputs are generated, and how systems respond. This Guide takes an alternative approach. It focuses on what is *not* asked, and what this absence reveals about how AI is currently integrated into human thinking and decision-making processes.

Across multiple systems and contexts, consistent patterns emerge in the omission of specific forms of inquiry. These include the absence of evaluation, limited self-interrogation, avoidance of adversarial thinking, underdevelopment of second-order reasoning, and the implicit treatment of boundaries.

These patterns are not random. They are structured, recurring, and shaped by interaction models, habits, incentives, and cognitive biases.

This Guide does not propose solutions or recommend changes in behaviour. Its objective is to make these patterns visible, to structure them clearly, and to situate them within a broader understanding of human–AI interaction.

Global Perspective / Neutrality Statement

This Guide adopts a global, system-agnostic perspective.

The observations presented are derived from interactions across multiple AI systems and are not specific to any single model, provider, or technological architecture. AISF does not rank, compare, or endorse AI systems, vendors, or platforms.

The purpose of this Guide is not to evaluate systems, but to examine patterns of use. The focus is on how AI is engaged, rather than on the capabilities of any particular system.

All interpretations are presented in a neutral and non-prescriptive manner. They reflect observed patterns at a specific point in time and are intended to support structured understanding rather than definitive conclusions.

Editorial Standard

This Guide follows AISF's institutional editorial standards:

• Observational, not prescriptive
• Neutral, non-endorsing, and globally applicable
• Structured and analytical in tone
• Free from advisory, instructional, or optimisation language

The content is designed to describe patterns, not to recommend actions. Where implications are discussed, they are presented as tendencies rather than predictions or directives.

All chapters are constructed as continuous narrative prose, maintaining clarity while avoiding simplification or compression of underlying concepts.

How to Use This Guide

This Guide is not intended to be read as a set of instructions or recommendations.

It is structured as a sequence of observations, each building on the previous to form a coherent understanding of how AI systems are currently engaged.

Readers may approach the Guide in one of two ways:

• **Sequential Reading** — to understand the full progression from observed gaps to systemic implications
• **Selective Reading** — to examine specific categories of absence or patterns of interaction

The value of the Guide lies not in any single chapter, but in the cumulative structure of the analysis.

Version & Governance

This publication forms part of the AISF AI Guidance Series and is issued under AISF's structured publication governance framework.

Each edition reflects a time-bound synthesis of observed patterns in AI interaction. As AI systems and usage patterns evolve, future editions may refine, extend, or update the observations presented.

AISF maintains a disciplined approach to version control, ensuring that updates are incorporated in a structured and transparent manner without retrospective alteration of prior editions.

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This publication is provided for informational and educational purposes only.

It presents a structured and time-bound analysis based on information available at the time of writing. The content reflects observed patterns, interpretations, and perspectives and does not constitute definitive, authoritative, or universally accepted conclusions.

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• financial, investment, or business advice
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• operational or strategic recommendations

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Artificial intelligence systems, technologies, and related terminology evolve rapidly. As such, the observations and interpretations contained in this publication may change over time and may not reflect subsequent developments.

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AISF publications are intended to support informed human judgment. Final responsibility for decisions, actions, and outcomes remains with the user.

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Chapter 1 — Framing the Absence: The Unasked Questions in AI Use

Across multiple globally deployed AI systems, a consistent pattern emerges that is not defined by what users ask, but by what they do not. This absence is not incidental. It is structured, repeatable, and observable across a wide range of interactions. While most analyses of AI usage focus on the presence of queries—what people are asking, how they are prompting, and the outputs they receive—the survey material reveals that the more informative signal lies elsewhere. It lies in the systematic absence of certain forms of questioning.

This absence becomes visible only when interactions are examined in aggregate. At the level of a single exchange, nothing appears missing. A user poses a question, the system responds, and the interaction concludes with an output that is often coherent, relevant, and contextually appropriate. There is no immediate indication that something has been overlooked. The interaction appears complete within its own frame. However, when large volumes of such interactions are considered together, patterns begin to emerge—not in the content of what is asked, but in the consistent omission of particular lines of inquiry.

In this context, absence functions as a structural signal. It is not the absence of random or isolated questions, but the absence of entire categories of questioning. These categories—such as questioning the limitations of outputs, examining underlying assumptions, or exploring alternative interpretations—are rarely activated within typical interactions. Their absence is consistent enough to form a pattern, and it is this pattern that provides insight into how AI systems are being used.

This mode of analysis differs from traditional approaches, which tend to focus on observable inputs and outputs. Conventional evaluation examines what is present: the quality of prompts, the accuracy of responses, or the efficiency of workflows. In contrast, the present framing considers what is systematically excluded from interaction. The distinction is subtle but significant. Presence reveals behaviour; absence reveals boundaries. It shows not only what users do, but the limits within which they operate.

The survey responses indicate that these boundaries are not consciously defined by users. They emerge through repeated patterns of interaction. Over time, certain types of questions become normalised, while others remain unarticulated. This results in a stable but constrained interaction space, within which users operate without necessarily recognising its limits.

One of the most prominent characteristics of this constrained space is the narrowing of inquiry. Users tend to approach AI systems with questions that are already framed in specific ways. These frames define what is being asked, what is considered relevant, and what falls outside the scope of the interaction. For example, a user may ask how to perform a task, evaluate an option, or generate a piece of content. Implicit within these questions are assumptions about the nature of the problem, the completeness of the available options, and the role of the AI system in providing a solution.

These frames are not constructed in isolation. They are shaped by prior experiences with information systems, including search engines, productivity tools, and structured workflows. Over time, these experiences establish expectations about how questions should be formulated and what kinds of responses are appropriate. When users interact with AI systems, they carry these expectations forward. The result is a continuity of interaction patterns, even though the underlying capabilities of AI systems differ significantly from those of earlier tools.

AI systems, in turn, tend to reinforce these frames. When presented with a well-formed question, they generate responses that align with the structure and assumptions embedded in that question. The response is tailored to the frame provided. It does not typically challenge the framing itself unless explicitly prompted to do so. This creates a form of alignment between user expectations and system behaviour. The interaction proceeds smoothly, and the output appears to address the question effectively.

However, this alignment has a secondary effect. It stabilises the initial frame and reduces the likelihood that it will be questioned. Because the response fits the question, the question itself is not revisited. Alternative framings are not explored, and the boundaries of the inquiry remain intact. Over repeated interactions, this process leads to a narrowing of inquiry in which users operate within increasingly familiar and unexamined frames.

This narrowing is not easily detected by users. From their perspective, the interaction is successful. The question is answered, the task is completed, and the output meets expectations. There is no immediate feedback indicating that alternative questions could have been asked or that the framing itself could have been reconsidered. The absence of such feedback contributes to the persistence of the pattern.

The reinforcing loop of output acceptance further strengthens this dynamic. AI systems are designed to produce outputs that are coherent, fluent, and contextually appropriate. These characteristics contribute to a perception of reliability. When an output is well-structured and aligns with the user’s expectations, it is more likely to be accepted without further interrogation. The coherence of the response reduces the perceived need for additional questioning.

This creates a feedback loop in which acceptance becomes the default response to output. The user asks a question, receives a coherent answer, and accepts it as sufficient. The interaction concludes without further exploration. Over time, this pattern reinforces itself. The user becomes accustomed to receiving satisfactory outputs, and the inclination to question those outputs diminishes.

Within this loop, trust begins to form. However, this trust is not necessarily based on systematic verification or critical evaluation. It is derived from repeated experiences of coherence and relevance. Because the outputs are consistently well-formed, they are perceived as reliable. This perception can develop before a deeper understanding of the system’s limitations is established.

The result is a form of premature trust. The system is treated as a dependable source of answers, even though the conditions under which those answers are generated may not be fully examined. This does not imply that the outputs are incorrect, but that the basis for trust is not explicitly articulated. It emerges implicitly through repeated interaction.

Alongside this, an illusion of completeness can arise. When a response appears thorough and well-structured, it can create the impression that all relevant aspects of the question have been addressed. The presence of detail, clarity, and logical flow contributes to this perception. However, completeness in presentation does not necessarily equate to completeness in coverage. Certain dimensions of the problem may remain unexamined, particularly those that fall outside the initial frame of the question.

Because these dimensions are not visible within the response, their absence is not immediately apparent. The interaction appears complete within its own boundaries. This reinforces the tendency to accept outputs at face value and reduces the likelihood of further inquiry.

Underlying these dynamics is a predominantly transactional model of interaction. Users approach AI systems in a manner similar to other digital tools. The interaction is framed as a sequence: a question is posed, a response is generated, and the exchange concludes. This model reflects established patterns from search engines and productivity software, where the objective is to obtain a specific output as efficiently as possible.

In this model, the interaction is discrete and bounded. Each query is treated as an independent transaction. There is limited expectation of iterative exploration or ongoing dialogue unless explicitly initiated by the user. The focus remains on the immediate task rather than on the broader context of reasoning or understanding.

This transactional framing influences how questions are formulated. Users tend to prioritise clarity, specificity, and efficiency. The objective is to obtain a useful response with minimal iteration. While this approach is effective for certain types of tasks, it also constrains the scope of interaction. It leaves limited space for questions that do not have immediate or clearly defined outputs.

The limitations of this model become apparent when considering the types of questions that are consistently absent. Questions that involve examining assumptions, exploring uncertainty, or considering alternative perspectives do not fit easily within a transactional structure. They often require iterative engagement, tolerance for ambiguity, and a willingness to extend the interaction beyond a single exchange.

These characteristics introduce friction into the interaction. Friction, in this context, refers to the additional cognitive and temporal effort required to engage with more complex forms of inquiry. Asking a question about uncertainty or failure conditions may lead to a response that is less definitive, more nuanced, or more complex than a straightforward answer. This can make the interaction feel less efficient.

Human interaction patterns tend to minimise such friction. There is a preference for clarity, speed, and resolution. Questions that lead to immediate and actionable outputs align with this preference. Questions that introduce ambiguity or require extended exploration do not. As a result, they are less frequently asked.

This tendency does not operate at the level of conscious decision-making in most cases. It is embedded in habitual patterns of interaction. Users gravitate toward forms of engagement that are familiar, efficient, and predictable. Over time, these patterns become stabilised, and alternative forms of questioning remain underdeveloped.

The cumulative effect of these dynamics is the emergence of a structured absence. The absence of certain questions is not random; it is the product of reinforcing patterns. Narrowed frames of inquiry, acceptance of coherent outputs, transactional interaction models, and friction avoidance all contribute to the same outcome: a consistent underrepresentation of deeper forms of questioning.

This absence does not present itself as failure of the system or the user. It is a characteristic of the interaction itself. It reflects how AI systems are being integrated into existing cognitive and behavioural patterns. The significance of this absence lies in what it reveals about those patterns—their boundaries, their limitations, and their underlying assumptions.

By framing absence as a central organising concept, it becomes possible to examine these patterns more closely. The chapters that follow will structure this absence in greater detail, identifying specific categories of unasked questions, exploring the factors that contribute to their absence, and examining the implications of these patterns over time.

Chapter 2 — From Tool to Cognitive Environment: A Structural Reframing

Across the surveyed responses, a consistent structural pattern emerges in how AI systems are positioned within human interaction. Despite their expanded capabilities, they are predominantly approached and utilised as tools. This positioning is not formally defined, yet it is reflected in the nature of the questions posed, the expectations of responses, and the manner in which interactions are concluded. The consequence is not merely a stylistic preference in usage, but a deeper structural constraint on how AI systems are engaged.

The notion of AI as a tool is not inaccurate in itself. AI systems perform functions, respond to inputs, and generate outputs in ways that resemble other digital instruments. However, the survey material indicates that this framing is incomplete. It captures only a subset of the system's potential modes of engagement. More significantly, it shapes the boundaries of interaction in ways that are not always visible to the user.

When AI is treated as a tool, the interaction model that follows is largely predefined. A tool is expected to perform a task when instructed. The user provides an input, the tool processes it, and an output is returned. This model emphasises execution. It assumes that the problem has already been defined, that the objective is clear, and that the primary role of the system is to assist in achieving that objective efficiently.

This structure aligns closely with established patterns from earlier technologies. Search engines, calculators, and productivity software all operate within similar paradigms. They are designed to respond to specific inputs with corresponding outputs, and their effectiveness is measured by speed, accuracy, and reliability within that framework. Users bring these expectations into their interactions with AI systems. As a result, AI is often integrated into existing workflows without a corresponding shift in how those workflows are conceptualised.

The survey responses suggest that this continuity of framing persists even when the capabilities of the system extend beyond those of traditional tools. AI systems are capable of iterative reasoning, contextual synthesis, and exploration of alternative perspectives. However, these capabilities are not inherently activated. They depend on the structure of the interaction. When the interaction is framed as a task-oriented exchange, the system responds within that frame. It generates outputs that align with the defined objective, without necessarily extending beyond it.

This creates a structural alignment between user expectations and system behaviour. The user expects a tool-like response, and the system provides one. The interaction proceeds smoothly, and the output appears satisfactory. However, this alignment also reinforces the initial framing. Because the system performs effectively within the tool paradigm, there is little impetus to reconsider that paradigm.

The concept of AI as a cognitive environment introduces a different structural perspective. Rather than viewing the system as a discrete instrument that performs tasks, this framing considers AI as a space within which thinking processes can occur. In this context, the interaction is not limited to input and output. It includes exploration, iteration, and the examination of ideas across multiple dimensions.

Within a cognitive environment, the boundaries of interaction are less rigid. Questions are not required to be fully defined at the outset. They can evolve through the interaction. The system can be engaged not only to produce answers, but to examine the structure of the question itself, to identify assumptions, and to explore alternative framings. This does not represent a different function of the system, but a different orientation toward its use.

The survey material indicates that this orientation is not commonly adopted. While individual instances of exploratory interaction can be observed, they are not the dominant pattern. Most interactions remain within the tool-based paradigm. The reasons for this are not explicitly stated by users, but they can be inferred from the consistency of the observed behaviour.

One contributing factor is the persistence of established mental models. Users have long been conditioned to interact with digital systems in transactional terms. The expectation that a system should respond to a clearly defined query with a specific answer is deeply embedded. This expectation provides a sense of control and predictability. It defines the interaction as bounded and manageable.

In contrast, engaging with AI as a cognitive environment introduces a degree of openness that is less familiar. The interaction may not lead to a single definitive output. It may involve multiple iterations, the exploration of uncertainty, and the consideration of alternative perspectives. This can alter the perceived efficiency of the interaction. The outcome is less immediately tangible, and the process itself becomes more prominent.

Another factor is the way in which AI systems present their outputs. Responses are typically delivered as complete and coherent units of information. This presentation reinforces the perception of the system as a provider of answers. The structure of the response suggests that the task has been completed. It does not inherently invite further exploration unless the user initiates it.

This presentation interacts with the existing tool-based framing to create a stable interaction pattern. The user asks a question, receives a complete response, and concludes the interaction. The system's ability to support extended reasoning or iterative exploration remains latent, activated only when the interaction deviates from this pattern.

The distinction between tool and cognitive environment is therefore not a binary classification, but a difference in emphasis. Both perspectives are valid within their respective contexts. The survey material does not indicate that one replaces the other. Instead, it highlights that one perspective is predominantly active, while the other remains underutilised.

This underutilisation has structural implications. When AI is consistently approached as a tool, the scope of interaction is constrained to predefined tasks. The system's role is limited to execution within those tasks. The possibility of using the system to examine the tasks themselves—to question their framing, to explore their assumptions, or to consider alternative approaches—remains largely unaddressed.

This constraint is not imposed by the system. It is a product of the interaction model. The system responds to the structure provided by the user. If the structure is task-oriented, the response will be task-oriented. If the structure allows for exploration, the response can extend accordingly. The observed pattern suggests that, in most cases, the structure provided is aligned with the tool paradigm.

The survey responses also indicate that this alignment is self-reinforcing. Successful task completion reinforces the perception that the tool-based approach is sufficient. There is no immediate feedback indicating that alternative modes of interaction could yield different forms of value. As a result, the existing pattern persists.

It is also notable that the cognitive environment framing does not naturally emerge from isolated interactions. It requires a shift in how interactions are sustained over time. Rather than treating each query as an independent transaction, the interaction becomes part of a broader process of exploration. This introduces continuity across exchanges, where each response informs subsequent questions.

In the absence of this continuity, the interaction remains segmented. Each exchange begins and ends within its own boundaries. The system's capacity to support cumulative reasoning is not engaged. The interaction does not extend beyond the immediate objective.

The survey material does not suggest that users are unaware of the system's broader capabilities. Rather, it indicates that these capabilities are not consistently integrated into interaction patterns. Awareness does not necessarily translate into structural change. The existing model of interaction remains dominant because it aligns with established habits, expectations, and perceptions of efficiency.

This structural reframing—from tool to cognitive environment—therefore serves to make visible a dimension of AI interaction that is currently implicit. It does not propose a replacement for the tool-based model, but it highlights the limitations of relying exclusively on that model. By examining how the system is positioned within interaction, it becomes possible to understand why certain forms of questioning remain absent.

The significance of this reframing lies in its connection to the patterns identified in Chapter 1. The absence of deeper questioning is not only a matter of individual behaviour. It is linked to the structural model through which the system is engaged. When the system is treated primarily as a tool, the range of questions that can be asked—and the forms of inquiry that are considered relevant—are correspondingly constrained.

This chapter establishes the structural context within which those absences occur. It identifies the prevailing interaction model and contrasts it with an alternative orientation that remains underdeveloped. The chapters that follow will continue to examine how this structural framing influences the types of questions that are asked, the gaps that emerge, and the implications of those gaps over time.

Chapter 3 — The Output Bias: Answers Over Judgment

Across the surveyed responses, a consistent behavioural pattern emerges in how AI systems are engaged: a pronounced orientation toward outputs. Users approach AI primarily as a means of obtaining answers, completing tasks, or generating artefacts. This orientation is not isolated to specific domains or user groups. It appears across a wide range of contexts, from simple informational queries to more complex forms of analysis and content generation.

This pattern can be described as an output bias. It reflects a prioritisation of results over the processes that produce them. In this framing, the value of interaction is measured by the quality, speed, and usability of the output. The internal reasoning that leads to that output—whether human or machine—is treated as secondary or, in many cases, remains unexamined.

The presence of this bias is not immediately evident at the level of individual interactions. Each exchange appears rational within its own context. A user poses a question with a defined objective, and the system provides a response that addresses that objective. The interaction achieves its intended purpose. However, when these interactions are considered collectively, a pattern becomes visible: the consistent absence of engagement with judgment.

Judgment, in this context, refers to the processes through which outputs are interpreted, evaluated, and contextualised. It involves assessing the relevance of information, identifying underlying assumptions, and determining how an output should be applied within a specific situation. While AI systems can generate content that appears to incorporate reasoning, the act of judgment remains structurally situated with the user. The survey material indicates that this dimension of interaction is underdeveloped.

Instead, users tend to treat outputs as endpoints. The response provided by the AI system is often accepted as a sufficient resolution to the query. The interaction concludes once the output meets a certain threshold of clarity or usefulness. There is limited continuation into questions that examine how the output was formed, what uncertainties it contains, or how it might change under different conditions.

This pattern is reinforced by the characteristics of the outputs themselves. AI-generated responses are typically fluent, structured, and contextually coherent. They are presented in a manner that resembles completed work products: essays, summaries, analyses, or recommendations. This presentation contributes to a perception of completeness. The output appears final, even when the underlying reasoning may be contingent or incomplete.

The survey responses highlight that users rarely interrogate this apparent completeness. Questions such as "What assumptions underlie this answer?" or "Under what conditions might this conclusion not hold?" are not commonly observed. Instead, the interaction tends to remain within the boundaries of the initial query. The output is treated as an answer rather than as a starting point for further examination.

This tendency can be traced to established patterns of information consumption. In many traditional contexts, obtaining an answer has been the primary objective. Educational systems, professional workflows, and digital tools have often emphasised the correctness and efficiency of outputs. Within these frameworks, the processes of reasoning and evaluation are either implicit or secondary.

When users engage with AI systems, these patterns persist. The system is positioned as a provider of answers, and the interaction is structured accordingly. The emphasis remains on obtaining a useful output with minimal iteration. This aligns with expectations of efficiency and productivity, which are frequently associated with the use of AI.

However, the survey material indicates that this orientation introduces a structural imbalance. While outputs are readily produced and consumed, the processes of judgment that give those outputs meaning are less frequently engaged. This imbalance is not necessarily recognised by users, as the outputs themselves often appear sufficient for immediate purposes.

The distinction between answer generation and judgment becomes more apparent when considering the nature of the questions that are asked. Many queries are framed in ways that assume the existence of a correct or optimal answer. For example, users may ask for the best approach, the most effective strategy, or the correct interpretation of a situation. These formulations direct the system toward producing definitive responses.

In contrast, questions that engage judgment tend to be less definitive. They may involve exploring multiple perspectives, examining trade-offs, or considering uncertainty. Such questions do not necessarily lead to a single answer. Instead, they open a space for interpretation and evaluation. The survey responses indicate that these forms of inquiry are less common.

The output bias also interacts with the temporal structure of interactions. Outputs provide immediate value. They can be used directly, shared, or applied to tasks. Judgment, by contrast, often requires additional time and cognitive effort. It involves reflection, comparison, and the integration of context. In environments where speed is prioritised, the emphasis on outputs becomes more pronounced.

This temporal dynamic contributes to the persistence of the bias. Users receive immediate benefits from output-oriented interactions, while the benefits of engaging judgment are less immediately visible. As a result, the interaction pattern that prioritises outputs is reinforced over time.

Another aspect of this pattern is the role of perceived expertise. AI systems are often perceived as possessing a broad base of knowledge and the ability to synthesise information effectively. This perception can lead to an implicit transfer of authority from the user to the system. When an output is presented in a confident and structured manner, it may be treated as authoritative.

The survey material suggests that this perception does not necessarily lead to explicit trust, but it does reduce the likelihood of active evaluation. The output is accepted as plausible, and the need for further questioning is diminished. This does not imply that users are unaware of potential limitations, but that the interaction does not consistently activate mechanisms for examining those limitations.

Within this context, the distinction between plausibility and validity becomes relevant. AI systems are capable of generating responses that are plausible within a given linguistic and contextual frame. However, plausibility does not guarantee validity in all contexts. The output bias tends to prioritise plausibility, as it aligns with the user's immediate expectations. The evaluation of validity requires additional engagement that is not consistently observed.

The survey responses also indicate that users rarely treat outputs as provisional. Instead, outputs are often integrated directly into workflows without explicit re-evaluation or decision-making processes. The absence of provisional framing means that the output is not explicitly positioned as subject to further validation or interpretation. This contributes to the perception of completeness and finality.

The cumulative effect of these dynamics is the establishment of a stable interaction pattern in which outputs are central and judgment is peripheral. This pattern does not emerge from a single factor, but from the interaction of multiple elements: the design of AI outputs, established habits of information consumption, expectations of efficiency, and the perceived authority of the system.

It is important to note that this pattern does not imply a lack of capacity for judgment on the part of users. Rather, it reflects how that capacity is engaged within the context of AI interaction. The survey material suggests that the interaction structure itself does not consistently prompt or require the activation of judgment. As a result, it remains underutilised.

This underutilisation has implications for how AI systems are integrated into broader processes. When outputs are treated as endpoints, the opportunity to use AI as a means of examining reasoning is not fully realised. The interaction remains focused on production rather than interpretation.

The output bias also contributes to the absence identified in Chapter 1. Questions that would engage judgment—such as those examining uncertainty, assumptions, or alternative perspectives—are less frequently asked. The interaction remains within the domain of answer generation, and the broader space of inquiry remains unexplored.

This chapter does not seek to reposition outputs or judgment as inherently superior to one another. Both are integral components of interaction. However, the observed pattern indicates an imbalance in their engagement. Outputs are consistently prioritised, while judgment remains implicit or secondary.

By identifying this bias, it becomes possible to examine its role in shaping interaction patterns. The chapters that follow will explore how this bias interacts with other structural factors, including the absence of evaluation, the avoidance of adversarial thinking, and the limited exploration of consequences. Together, these patterns contribute to a broader understanding of how AI is currently used and what remains outside the frame of interaction.

Chapter 4 — The Missing Layer: Evaluation, Uncertainty, and Failure Conditions

Across the surveyed responses, a recurring structural gap becomes visible between the generation of outputs and the interpretation of those outputs. While users frequently engage AI systems to produce answers, analyses, and artefacts, there is a consistent under-engagement with the layer that sits between output and application. This layer can be described as evaluation—specifically, the examination of uncertainty, the identification of limitations, and the consideration of conditions under which an output may fail.

This missing layer is not defined by a lack of capability within AI systems. The survey material indicates that systems are able to articulate uncertainty, identify potential weaknesses, and explore conditions in which a response may not hold. However, these dimensions are rarely activated in typical interactions. The interaction often concludes once an output has been produced, without extending into an examination of how that output should be understood.

Evaluation, in this context, is not limited to determining whether an answer is correct or incorrect. It involves a broader set of processes that situate the output within a range of possible interpretations. It includes assessing the confidence of the response, identifying assumptions that underpin it, and understanding the boundaries within which it remains applicable. These processes are distinct from the act of generating the output itself, and they require a different form of engagement.

The survey responses suggest that this distinction is not consistently maintained in practice. Outputs are often treated as self-contained units of information. The clarity and structure of the response contribute to a perception that the necessary reasoning has already been completed. As a result, the additional step of evaluating the output is not always initiated.

One of the key dimensions of this missing layer is uncertainty. AI systems operate by generating responses that are plausible within a given context, based on patterns in their training data. This process inherently involves uncertainty. However, the representation of this uncertainty is not always explicit in the output. Responses are typically presented in a confident and declarative manner, even when the underlying information may be contingent or incomplete.

The survey material indicates that users do not frequently probe this dimension. Questions that seek to understand how certain an answer is, what information may be missing, or how the response might vary under different conditions are not commonly observed. Instead, the interaction tends to accept the output at face value, without explicitly engaging with its uncertainty.

This absence is not necessarily a result of misunderstanding. Rather, it reflects how the interaction is structured. The initial query is often framed in a way that seeks a definitive answer. The system responds accordingly, producing a response that aligns with that expectation. The interaction concludes within this frame, and the opportunity to explore uncertainty remains unaddressed.

Closely related to uncertainty is the concept of failure conditions. These refer to the circumstances under which an output may not hold true or may lead to unintended consequences. Identifying failure conditions requires moving beyond the surface of the response to consider its limitations. It involves asking how the output might break down, what assumptions it depends on, and how it might behave in different contexts.

The survey responses indicate that such questioning is relatively rare. Users tend to focus on whether an output can be used, rather than on how it might fail. This orientation aligns with the output bias identified in the previous chapter, where the emphasis is placed on obtaining a usable result. The examination of failure conditions introduces a different perspective, one that is less oriented toward immediate application and more toward understanding the robustness of the response.

The absence of this perspective has structural implications. Without an explicit consideration of failure conditions, outputs may be applied in contexts where their underlying assumptions do not hold. This does not necessarily result in immediate errors, but it can lead to subtle misalignments between the output and the situation in which it is used. These misalignments may not be immediately visible, particularly when the output appears coherent and relevant.

Another dimension of the missing layer is the evaluation of underlying assumptions. AI-generated responses often incorporate implicit assumptions about context, data, and objectives. These assumptions are not always articulated within the response. They are embedded in the way the output is constructed. The survey material suggests that users do not consistently interrogate these assumptions.

This can be understood as an extension of the transactional interaction model described in earlier chapters. When the interaction is framed as a means of obtaining an answer, the focus remains on the answer itself. The processes that generate the answer, including the assumptions that shape it, are not foregrounded. As a result, they remain implicit.

The lack of engagement with assumptions contributes to the perception of completeness. When an output is presented without visible gaps or contradictions, it appears self-sufficient. The absence of explicit assumptions reinforces this perception. The response does not signal that it is contingent on particular conditions, and therefore it is not immediately treated as such.

This dynamic is further reinforced by the way AI systems present information. Responses are typically structured to be helpful and coherent. They are organised in a way that facilitates understanding and application. While this structure enhances usability, it can also obscure the provisional nature of the information. The response appears final, even when it is not.

The survey responses highlight that users rarely request explicit articulation of these underlying elements. Questions that would surface assumptions, uncertainties, or failure conditions are not commonly observed. This does not imply that users are incapable of engaging with these dimensions, but that the interaction does not consistently prompt such engagement.

The missing layer of evaluation can therefore be understood as a gap between the generation of outputs and their integration into decision-making or action. It is a layer that requires deliberate engagement, but one that is not structurally embedded in typical interaction patterns.

This gap also interacts with the formation of trust. As noted in earlier chapters, repeated exposure to coherent and relevant outputs can lead to the development of trust in the system. When evaluation is not consistently activated within interaction, this trust is based primarily on the surface characteristics of the output. The underlying uncertainties and limitations are not systematically incorporated into the user's perception.

This does not necessarily lead to immediate issues. In many cases, the outputs are sufficiently accurate or useful for their intended purpose. However, the absence of evaluation means that the boundaries of this usefulness are not clearly defined. The user may not have a structured understanding of when the output is reliable and when it may not be.

The survey material also suggests that the absence of evaluation is linked to the perception of effort. Engaging with uncertainty and failure conditions requires additional cognitive work. It involves questioning the response, considering alternative scenarios, and integrating contextual knowledge. In contrast, accepting an output as sufficient allows the interaction to conclude more quickly.

This difference in effort contributes to the persistence of the gap. Interactions that minimise effort are more likely to be repeated, particularly in environments where efficiency is prioritised. Over time, this leads to a stabilisation of patterns in which evaluation is consistently underrepresented.

It is important to recognise that this missing layer is not a separate stage that exists independently of the interaction. It is a dimension of the interaction that can be engaged or not engaged. The survey responses indicate that, in most cases, it is not engaged. The interaction remains at the level of output generation, and the deeper examination of that output does not occur.

This chapter does not seek to resolve this gap, but to describe it as a structural feature of current AI use. By identifying the absence of evaluation, uncertainty, and failure condition analysis, it becomes possible to understand how outputs are being interpreted and applied. This understanding provides a foundation for examining related gaps, including the limited use of adversarial thinking and the under-exploration of consequences.

The missing layer is therefore not an isolated phenomenon. It is part of a broader pattern in which certain forms of inquiry remain outside the dominant interaction model. By making this layer visible, it becomes possible to examine how it interacts with other structural elements of AI use and how it contributes to the overall shape of human–AI interaction.

Chapter 5 — The Unasked Questions of Self-Interrogation

Across the surveyed responses, a distinct pattern emerges in the direction of inquiry. Users predominantly direct questions outward—toward problems, tasks, or external situations—rather than inward toward their own thinking processes. AI systems are engaged to generate answers, provide explanations, or assist in execution, but they are less frequently used as a means of examining the reasoning, assumptions, or cognitive patterns of the user themselves.

This pattern reveals a structural absence of self-interrogation within AI interaction. While the systems are capable of engaging with questions about reasoning, bias, and perspective, such questions are not commonly posed. The interaction remains focused on external problem-solving, with limited extension into the examination of how the problem is being understood in the first place.

Self-interrogation, in this context, refers to the process of examining one's own thinking. It involves identifying assumptions, recognising patterns in reasoning, and exploring how conclusions are formed. It is distinct from asking for information or solutions. It requires turning the focus of inquiry inward, using the system not only as a source of answers, but as a means of reflecting on the structure of one's own cognition.

The survey material indicates that this mode of engagement is underrepresented. Users rarely ask questions that would surface their own assumptions or challenge their perspective. Instead, questions tend to assume that the framing of the problem is already appropriate. The role of the system is to operate within that frame, not to examine it.

This absence is not immediately visible within individual interactions. A user may receive a useful answer, apply it successfully, and perceive the interaction as complete. There is no immediate indication that an alternative line of questioning—one that examines the user's own reasoning—could have been pursued. As with other forms of absence identified in earlier chapters, the pattern becomes apparent only when interactions are considered collectively.

One aspect of this pattern is the implicit stability of the user's perspective. When questions are directed outward, the user's framing of the problem remains unchallenged. The system responds to the question as posed, aligning with the assumptions embedded within it. This creates a form of confirmation, not necessarily of correctness, but of coherence. The response fits the question, and the interaction proceeds without disruption.

The survey responses suggest that users do not consistently use AI systems to disrupt this coherence. Questions that would introduce alternative perspectives, highlight blind spots, or challenge the initial framing are less common. The interaction remains within the boundaries defined by the user's original perspective.

This dynamic is closely related to the transactional model of interaction described in earlier chapters. When the objective is to obtain an answer, the question is framed in a way that facilitates that outcome. There is limited incentive to question the framing itself, as doing so may complicate the interaction or extend its duration. The focus remains on resolution rather than reflection.

Another dimension of the absence of self-interrogation is the limited examination of cognitive biases. AI systems can be used to identify patterns in reasoning that may not be immediately visible to the user. They can highlight tendencies such as confirmation bias, overgeneralisation, or selective attention. However, the survey material indicates that such uses are not commonly observed.

Instead, users tend to rely on their own judgment without explicitly examining how that judgment is formed. The system is used to support decisions, but not to analyse the cognitive processes that lead to those decisions. This creates a separation between the use of AI for external problem-solving and the examination of internal reasoning.

This separation is not necessarily intentional. It reflects the way in which AI systems are conceptualised within interaction. As noted in previous chapters, the system is often treated as a tool for producing outputs. Within this framing, the focus remains on the task at hand. The user's own thinking is not positioned as an object of inquiry.

The survey responses also indicate that users rarely ask AI systems to analyse patterns across multiple interactions. Over time, users develop recurring approaches to problem-solving, decision-making, and information interpretation. These patterns can be identified and examined, but doing so requires a shift from single-instance queries to a more cumulative form of engagement.

Such cumulative analysis is not commonly observed. Interactions are typically treated as discrete events, each focused on a specific question. The continuity required to examine patterns in thinking is therefore not established. The system's capacity to identify and reflect on these patterns remains largely unutilised.

The absence of self-interrogation also interacts with the perception of expertise. When users engage AI systems for answers, the system is positioned as a source of knowledge or synthesis. The user's role is to interpret and apply the output. This dynamic can obscure the fact that the framing of the question—and the interpretation of the response—are equally important components of the interaction.

By not examining their own role in shaping the interaction, users may not fully recognise how their assumptions influence the outputs they receive. The system responds to the information and structure provided by the user. If that structure contains implicit biases or limitations, these are likely to be reflected in the response. Without self-interrogation, this reflection may not be recognised.

Another contributing factor to this pattern is the discomfort associated with examining one's own thinking. Self-interrogation can introduce uncertainty, as it involves questioning assumptions that may have been taken for granted. It may reveal inconsistencies or gaps in reasoning. In contrast, asking for answers or solutions provides a more direct and less ambiguous form of engagement.

The survey material suggests that users tend to favour interactions that provide clarity and resolution. Questions that lead to self-examination may not align with this preference. They may require additional cognitive effort and may not produce a single, definitive outcome. As a result, they are less frequently pursued.

This tendency is reinforced by the absence of explicit prompts for self-interrogation within typical interactions. AI systems respond to the questions they are given. If those questions do not involve examining the user's own thinking, the system does not consistently introduce that dimension on its own. The interaction remains aligned with the user's initial intent.

The cumulative effect of these dynamics is the formation of a stable pattern in which self-interrogation is consistently underrepresented. The interaction remains focused on external problems, with limited engagement in examining how those problems are understood.

This absence has implications for how AI systems are integrated into broader processes of reasoning and decision-making. When the user's own thinking is not examined, the interaction remains one-sided. The system provides outputs, but the framework within which those outputs are interpreted remains unchallenged.

It is important to note that this pattern does not imply a deficiency in users' ability to engage in self-interrogation. Rather, it reflects how that ability is activated within the context of AI interaction. The survey responses indicate that the interaction structure does not consistently prompt or require this form of engagement.

This chapter identifies the absence of self-interrogation as a distinct category of unasked questions. It highlights how the direction of inquiry—outward rather than inward—shapes the interaction and contributes to the broader patterns identified in this Guide.

By making this absence visible, it becomes possible to examine how it interacts with other structural gaps, including the limited use of adversarial thinking and the under-exploration of consequences. Together, these patterns provide a more comprehensive understanding of how AI systems are currently engaged and what dimensions of interaction remain underdeveloped.

Chapter 6 — The Avoidance of Adversarial Thinking

Across the surveyed responses, a consistent pattern emerges in how users position AI systems in relation to their own ideas, plans, and decisions. The interaction is predominantly confirmatory rather than adversarial. Users tend to engage AI systems to generate, refine, or support their thinking, but far less frequently to challenge, critique, or stress-test it.

This pattern reflects a broader absence of adversarial thinking within AI interaction. Adversarial thinking, in this context, refers to the deliberate use of inquiry to expose weaknesses, identify risks, and explore counterarguments. It involves engaging with ideas not to validate them, but to examine their limits. While AI systems are capable of supporting this form of engagement, the survey material indicates that it is not commonly activated.

The absence of adversarial thinking is not immediately apparent within individual interactions. A user may present an idea or plan, receive a structured response, and perceive the exchange as productive. The response may include refinements, elaborations, or supportive reasoning. However, it often operates within the same conceptual frame as the original query. The system aligns with the direction of the question, rather than introducing structured opposition to it.

This alignment is not a limitation of the system itself. AI systems can generate counterarguments, simulate opposing perspectives, and identify potential points of failure when prompted to do so. The observed pattern instead reflects how the interaction is initiated and sustained. When the initial query is framed in a way that seeks validation or improvement, the response follows that trajectory.

This creates a form of directional consistency within the interaction. The user's perspective sets the direction, and the system reinforces it through coherent and relevant outputs. The interaction proceeds without introducing significant tension or contradiction. The absence of such tension is often interpreted as a sign of clarity or alignment, rather than as an indication that alternative perspectives have not been explored.

The survey responses indicate that users do not consistently initiate interactions that are explicitly adversarial. Questions that would position the system as a critic, a challenger, or an opposing agent are less frequently observed. Instead, the system is positioned as a collaborator or assistant. This positioning shapes the nature of the responses that are generated.

This pattern can be understood in relation to the broader interaction models identified in earlier chapters. The transactional model emphasises efficiency and resolution. Within this model, adversarial thinking introduces additional steps. It requires the exploration of alternative perspectives, the identification of weaknesses, and the consideration of outcomes that may not align with the user's initial objective. These processes extend the interaction and introduce complexity.

As a result, adversarial engagement can be perceived as less efficient. It may not lead directly to a usable output, and it may complicate the decision-making process. In environments where speed and clarity are prioritised, this additional complexity may be avoided. The interaction remains focused on producing a coherent and actionable result.

Another contributing factor is the role of cognitive comfort. Adversarial thinking involves engaging with potential flaws, risks, and uncertainties. It requires a willingness to examine ideas in ways that may challenge existing assumptions or reveal weaknesses. The survey material suggests that users tend to avoid interactions that introduce this form of cognitive friction.

This avoidance is not necessarily conscious. It is embedded in habitual patterns of inquiry. Questions are often framed to produce constructive or supportive responses. The system is engaged to assist in achieving a desired outcome, rather than to question the desirability or feasibility of that outcome. Over time, this leads to a stabilisation of interaction patterns in which adversarial questioning remains underrepresented.

The absence of adversarial thinking also interacts with the output bias described in Chapter 3. When the focus of interaction is on generating answers, there is less emphasis on examining the robustness of those answers. Outputs are evaluated in terms of clarity and usefulness, rather than in terms of their ability to withstand critique. The system provides a response that appears complete, and the interaction concludes without further examination.

This dynamic is reinforced by the presentation of AI-generated outputs. Responses are typically structured in a way that emphasises coherence and logical flow. They present arguments, explanations, or recommendations in a manner that appears internally consistent. This presentation can create the impression that the reasoning has been thoroughly considered.

However, the survey responses indicate that this internal consistency is not frequently tested through adversarial questioning. Users do not consistently ask how the reasoning might break down, what counterarguments exist, or how the conclusions might change under different assumptions. The interaction remains within the boundaries of the initial framing.

The absence of adversarial thinking also limits the exploration of alternative perspectives. AI systems can simulate viewpoints from different stakeholders, disciplines, or contexts. They can present competing interpretations of a situation. However, these capabilities are typically activated only when explicitly requested. In the absence of such requests, the interaction remains aligned with the user's initial perspective.

This alignment can create a form of perspective reinforcement. The system's responses reflect and elaborate on the user's framing, without introducing significant divergence. Over time, this can contribute to a narrowing of perspective, where alternative viewpoints are not systematically considered.

The survey material suggests that this pattern is particularly pronounced in contexts where the user has a defined objective or preferred outcome. In such cases, the interaction is oriented toward achieving that outcome. Questions are framed to support progress in a specific direction, and responses are evaluated based on their alignment with that direction.

Adversarial thinking, by contrast, introduces the possibility that the direction itself may need to be reconsidered. It shifts the focus from execution to examination. This shift is not commonly observed in typical interactions, as it does not align with the immediate objective of obtaining a result.

Another dimension of the absence of adversarial thinking is the limited exploration of failure scenarios. While users may ask how to achieve a particular outcome, they less frequently ask how that outcome might fail. Questions that would examine the weakest points of a plan, the most likely sources of error, or the conditions under which an approach may not succeed are not commonly observed.

This absence is closely related to the missing layer of evaluation identified in Chapter 4. Without examining failure conditions, the robustness of an output or plan is not fully understood. The interaction remains focused on what works, rather than on what might not.

The cumulative effect of these dynamics is the emergence of a stable interaction pattern in which adversarial thinking is consistently underrepresented. The system is positioned as a supportive agent, the interaction is oriented toward producing coherent outputs, and the exploration of weaknesses or counterarguments is limited.

It is important to note that this pattern does not reflect an inherent limitation in users or systems. It reflects how the interaction is structured and sustained. The survey responses indicate that when adversarial questions are posed, AI systems are capable of engaging with them effectively. The limitation lies in the frequency with which such questions are initiated.

The absence of adversarial thinking therefore represents a category of unasked questions. It highlights a dimension of interaction that remains outside the dominant pattern of use. By identifying this absence, it becomes possible to examine how it interacts with other structural elements, including the narrowing of inquiry, the output bias, and the missing layer of evaluation.

This chapter does not propose an alternative mode of interaction, but it makes visible a structural feature of current AI use. The avoidance of adversarial thinking is not an isolated phenomenon. It is part of a broader pattern in which certain forms of inquiry—those that introduce tension, complexity, or uncertainty—are less frequently engaged.

The chapters that follow will continue to examine how these patterns extend into other areas, including the limited exploration of consequences and the underdevelopment of meta-learning. Together, these observations contribute to a more comprehensive understanding of how AI systems are currently used and what remains outside the frame of interaction.

Chapter 7 — The Absence of Second-Order Thinking

Across the surveyed responses, a recurring limitation becomes visible in how users engage with the implications of AI-generated outputs. Interactions tend to focus on immediate results—what can be done, what answer is provided, or what conclusion is reached—while the exploration of subsequent effects remains underdeveloped. This pattern reflects a broader absence of second-order thinking within AI interaction.

Second-order thinking, in this context, refers to the examination of consequences beyond the immediate outcome. It involves asking not only what happens as a direct result of an action or decision, but what follows from that result, and how those subsequent effects may evolve over time. This form of thinking introduces a temporal and systemic dimension to inquiry, extending beyond the initial answer.

The survey material indicates that such extension is not commonly observed. Users tend to frame questions in ways that seek resolution at the first level. For example, a query may ask for the best approach to a problem, the most effective strategy, or the likely outcome of a decision. The system responds within this frame, providing a structured answer that addresses the immediate question. The interaction often concludes at this point, without progressing into further layers of consequence.

This pattern can be understood as a form of first-order orientation. The interaction is designed to produce an answer that is directly applicable to the question posed. The output is evaluated based on its clarity, relevance, and usability within the immediate context. The exploration of what happens next—how the situation evolves after the initial step—is not consistently integrated into the interaction.

The absence of second-order thinking is not attributable to a lack of capability within AI systems. The survey responses indicate that systems can simulate future scenarios, map causal chains, and explore downstream effects when prompted. However, these capabilities are not automatically activated. They depend on the structure of the question. When the question is limited to first-order outcomes, the response remains within that scope.

This creates a structural boundary within the interaction. The system operates within the temporal frame defined by the user. If that frame is limited to the immediate outcome, the interaction does not extend beyond it. The possibility of examining subsequent consequences remains latent.

One of the key characteristics of second-order thinking is its iterative nature. It requires moving beyond a single answer to consider how that answer interacts with other variables over time. This may involve examining feedback loops, unintended consequences, or shifts in context that alter the initial conditions. Such exploration introduces complexity into the interaction, as it requires holding multiple layers of cause and effect simultaneously.

The survey material suggests that users do not consistently engage with this level of complexity. Questions are often structured to produce a clear and direct response. The introduction of multiple layers of consequence may reduce the perceived clarity of the output. Instead of a single answer, the response may present a range of possibilities, each contingent on different conditions. This can make the interaction less straightforward.

This dynamic aligns with the broader pattern of friction avoidance identified in earlier chapters. Second-order thinking introduces cognitive and temporal friction. It requires additional effort to formulate questions, interpret responses, and integrate multiple outcomes. In contrast, first-order questions align with expectations of efficiency and resolution. They produce outputs that can be more readily applied.

Another factor contributing to the absence of second-order thinking is the way in which problems are framed. Many queries assume a static context in which the variables remain stable. The objective is to identify the optimal action within that context. However, in practice, contexts are often dynamic. Actions taken at one point can alter the conditions under which future decisions are made.

The survey responses indicate that this dynamic aspect is not consistently incorporated into AI interactions. Questions are often framed as if the situation is fixed, rather than evolving. As a result, the responses address the problem as defined, without extending into how the problem itself may change over time.

This limitation is particularly evident in scenarios involving decision-making. Users may ask for recommendations or strategies based on current conditions. The system provides an answer that aligns with those conditions. However, the interaction does not consistently explore how the recommended action might influence future conditions, or how those changes might require subsequent adjustments.

The absence of this exploration can lead to a form of partial understanding. The initial decision may appear sound within the immediate frame, but its longer-term implications remain unexamined. This does not necessarily result in incorrect decisions, but it limits the visibility of potential trade-offs or unintended outcomes.

The survey material also highlights the limited use of AI systems for mapping causal chains. While users may ask about direct effects, they less frequently ask how those effects propagate through a system. Questions that would trace the sequence of events following an action—examining how one outcome leads to another—are not commonly observed.

This absence can be linked to the transactional model of interaction. When each query is treated as a discrete event, there is limited continuity across exchanges. The interaction begins and ends with the immediate question. The extension into subsequent stages requires a shift from transactional to iterative engagement, which is not the dominant pattern.

The cumulative effect of these dynamics is the emergence of a stable interaction pattern in which second-order thinking remains underrepresented. The focus remains on immediate outputs, and the exploration of downstream consequences is limited.

It is also notable that the absence of second-order thinking interacts with other gaps identified in this Guide. For example, the output bias prioritises immediate answers, while the missing layer of evaluation limits the examination of uncertainty. Together, these patterns create an interaction environment in which the temporal dimension of consequences is not consistently engaged.

Similarly, the avoidance of adversarial thinking reduces the likelihood of exploring negative or unintended outcomes. Without adversarial questioning, the interaction remains focused on what works, rather than on what might go wrong. This further limits the exploration of second-order effects.

The absence of second-order thinking also influences how users perceive the completeness of an interaction. When a question is answered at the first level, the interaction appears resolved within its immediate frame. The output provides a sense of closure. However, this closure is based on a limited temporal frame. The broader sequence of events that may follow is not incorporated into the perception of completeness.

This dynamic can reinforce the tendency to treat outputs as endpoints, rather than as starting points for further exploration. The interaction concludes once the immediate question is addressed, and the opportunity to examine subsequent implications is not pursued.

It is important to recognise that second-order thinking does not always produce definitive answers. It often introduces a range of possibilities, each dependent on different conditions. This can make the interaction more complex and less conclusive. The survey responses suggest that users tend to favour interactions that provide clarity and resolution, which may contribute to the underrepresentation of this form of inquiry.

This chapter identifies the absence of second-order thinking as a distinct structural feature of current AI use. It highlights how the temporal dimension of consequences is not consistently integrated into interactions, and how this absence shapes the overall pattern of inquiry.

By making this absence visible, it becomes possible to examine how it interacts with other structural elements, including the framing of questions, the evaluation of outputs, and the avoidance of adversarial engagement. Together, these patterns provide a more comprehensive understanding of how AI systems are currently used and what dimensions of reasoning remain outside the dominant interaction model.

Chapter 8 — The Underdevelopment of Meta-Learning

Across the surveyed responses, a further structural pattern becomes visible in how AI systems are engaged over time. While users frequently interact with AI to obtain answers, generate outputs, and support immediate tasks, there is limited evidence of sustained engagement with the process of learning how to think with AI itself. This pattern reflects the underdevelopment of meta-learning within AI interaction.

Meta-learning, in this context, refers to the examination and refinement of one's own approach to learning, reasoning, and interacting with AI systems. It involves understanding not only the content of what is being generated, but the processes through which that content is produced and interpreted. It includes recognising patterns in one's own usage, identifying limitations in interaction strategies, and adapting those strategies over time.

The survey material indicates that this dimension of interaction is not consistently engaged. Users tend to focus on the immediate objective of each interaction—obtaining an answer, completing a task, or generating an output—rather than on how their approach to the interaction itself could be examined or refined. Each exchange is treated as an independent event, rather than as part of a cumulative learning process.

This pattern can be understood in relation to the broader interaction models identified in earlier chapters. The transactional model, which emphasises discrete exchanges and immediate outputs, does not inherently support meta-learning. When each interaction is self-contained, there is limited continuity across exchanges. The user does not necessarily reflect on how previous interactions have shaped current ones, or how their approach could evolve.

As a result, the interaction remains at the level of execution. The system is used to perform tasks or provide information, but the process of engaging with the system is not itself treated as an object of inquiry. The user's role in shaping the interaction—through the framing of questions, the interpretation of responses, and the integration of outputs—remains largely implicit.

The survey responses suggest that users rarely ask questions that would surface this process. Queries such as how their questioning patterns influence the outputs they receive, or how their interaction style could be adjusted to explore different dimensions of a problem, are not commonly observed. Instead, the focus remains on the immediate content of the response.

This absence is not immediately visible within individual interactions. Each exchange may appear effective within its own context. The user receives a useful output, applies it, and moves on to the next task. There is no immediate indication that the interaction itself could be examined or improved. The absence of meta-learning becomes apparent only when interactions are viewed collectively over time.

One aspect of this pattern is the limited use of feedback loops. In many forms of learning, feedback is a central mechanism through which understanding is refined. It involves comparing outcomes with expectations, identifying discrepancies, and adjusting behaviour accordingly. The survey material indicates that such feedback loops are not consistently established within AI interaction.

While users may evaluate the usefulness of an output, this evaluation is often confined to the immediate context. The broader question of how the interaction produced that output—what aspects of the query were effective, what assumptions were embedded, and how the process could be adjusted—is not consistently explored. The interaction does not extend into a systematic examination of its own structure.

Another dimension of the underdevelopment of meta-learning is the limited examination of interaction patterns over time. Users often engage with AI systems repeatedly, developing implicit habits in how they formulate questions and interpret responses. These habits can shape the nature of the outputs they receive. However, the survey responses suggest that these patterns are not frequently made explicit.

The system is capable of identifying recurring themes, biases, or tendencies in user interactions when prompted. It can analyse sequences of queries and highlight patterns that may not be immediately apparent. However, such uses are not commonly observed. The interaction remains focused on the current query, rather than on patterns that span multiple exchanges.

This absence of pattern recognition contributes to the stability of existing interaction habits. Without explicit examination, users continue to engage with the system in similar ways, reinforcing established patterns. The potential for variation or adaptation remains underutilised.

The underdevelopment of meta-learning also interacts with the perception of AI systems as static entities. Users may perceive the system as having a fixed set of capabilities, rather than as a dynamic environment that can be engaged in different ways. This perception influences how interactions are structured. If the system is viewed as static, there is less emphasis on adapting one's approach to engage different aspects of its capabilities.

In contrast, meta-learning involves recognising that the effectiveness of interaction is not solely determined by the system, but also by how it is engaged. It requires an awareness of the interaction as a process that can be shaped and refined. The survey material suggests that this awareness is not consistently activated.

Another contributing factor is the emphasis on immediate productivity. AI systems are often used to enhance efficiency, enabling users to complete tasks more quickly. This emphasis on speed can reduce the perceived value of reflecting on the interaction process. Time spent examining how an interaction could be improved may not align with the immediate objective of completing a task.

This dynamic reinforces the focus on outputs. The interaction is evaluated based on what it produces, rather than on how it is conducted. Meta-learning, which operates at the level of process, remains peripheral within this evaluation framework.

The absence of meta-learning also limits the development of transferable understanding. When users focus solely on obtaining answers, they may not develop the underlying frameworks that allow them to apply knowledge across different contexts. AI systems can support the construction of such frameworks, but this requires engagement beyond the immediate output.

The survey responses indicate that users do not consistently use AI systems to build or refine these frameworks. Questions are often specific to a particular task or problem, rather than oriented toward general principles or patterns. As a result, the interaction remains context-specific, and the potential for broader learning is not fully realised.

This pattern can be linked to the absence of cumulative interaction. When each query is treated as independent, there is limited opportunity to build on previous exchanges. The interaction does not develop over time in a way that supports deeper understanding. Instead, it remains a series of isolated events.

The cumulative effect of these dynamics is the emergence of a stable interaction pattern in which meta-learning is underdeveloped. The system is used extensively, but the process of using the system is not systematically examined or refined. The interaction remains focused on immediate outputs, and the broader process of learning how to think with AI remains implicit.

It is important to note that this pattern does not imply a lack of capacity for meta-learning. The survey material suggests that when users engage with AI in ways that examine their own interaction patterns, the system can support this process effectively. The limitation lies in the frequency with which such engagement is initiated.

The underdevelopment of meta-learning therefore represents another category of unasked questions. It highlights a dimension of interaction that remains outside the dominant pattern of use. By identifying this absence, it becomes possible to examine how it interacts with other structural gaps, including the absence of self-interrogation, the avoidance of adversarial thinking, and the limited exploration of consequences.

This chapter does not seek to redefine the purpose of AI interaction, but to describe a structural feature of how it is currently used. The absence of meta-learning is not an isolated phenomenon. It is part of a broader pattern in which certain forms of inquiry—those that examine the process of thinking itself—are less frequently engaged.

The chapters that follow will continue to explore how these patterns extend into other areas, including the boundaries of AI use and the structural causes that underpin these gaps. Together, these observations contribute to a more comprehensive understanding of how AI systems are integrated into human thinking processes and what dimensions of that integration remain underdeveloped.

Chapter 9 — The Boundaries of AI Use: What Is Not Asked

Across the surveyed responses, a further structural absence becomes visible in how users engage with the limits of AI systems. While attention is consistently directed toward what AI can do—its capacity to generate outputs, synthesise information, and assist with tasks—there is comparatively limited engagement with what should remain outside its use. This absence is not framed as error or misuse, but as a lack of explicit questioning about boundaries.

This pattern reflects a broader orientation within AI interaction: capability is foregrounded, while appropriateness is assumed. Once an interaction begins, the use of AI is treated as given. The question becomes how the system can contribute, rather than whether its contribution is aligned with the nature of the task, the context in which it is applied, or the implications that may follow.

Boundaries, in this context, are not limited to technical constraints. They include situational, relational, and structural considerations that define where AI-generated outputs may be incomplete, insufficient, or misaligned with the requirements of a given context. These considerations are not always visible within the output itself. They exist at the level of interpretation and application, requiring a form of inquiry that is distinct from asking for answers.

The survey material indicates that this form of inquiry is not consistently activated. Users rarely pose questions that explicitly examine the limits of AI use. Instead, interactions proceed under an implicit assumption of universal applicability. The system is engaged, and its outputs are integrated into the user's workflow without systematic examination of whether that engagement is appropriate for the specific situation.

One aspect of this absence is the limited differentiation between contexts of varying significance. Interactions involving routine or low-stakes tasks are structurally similar to those involving more complex or consequential decisions. The system is approached in the same way, and the outputs are treated with a similar level of acceptance. The survey responses suggest that users do not consistently adjust their engagement with AI based on the potential impact of the outcome.

This uniformity of interaction contributes to the under-examination of boundaries. When the same interaction model is applied across contexts, the distinctions that define those contexts are not foregrounded. The interaction remains focused on functionality, and the question of whether AI should be used in a particular instance is not explicitly addressed.

Another dimension of boundary-related absence is the limited consideration of irreversibility. Certain actions or decisions produce outcomes that cannot be easily undone. In such contexts, the role of AI-generated outputs may require a different form of scrutiny. However, the survey material indicates that users do not consistently differentiate between reversible and irreversible contexts when engaging with AI systems. The interaction structure remains unchanged, regardless of the potential permanence of the outcome.

This absence is closely related to the patterns identified in earlier chapters. The output bias prioritises immediate results, while the missing layer of evaluation limits the examination of uncertainty and failure conditions. Together, these patterns create an interaction environment in which the boundaries of use are not actively examined. The focus remains on what the system can produce, rather than on the conditions under which those outputs should be applied.

The survey responses also highlight the limited engagement with relational contexts. AI systems are capable of generating responses that simulate aspects of human interaction, including tone, empathy, and reasoning. However, the use of such outputs in situations involving trust, interpersonal dynamics, or emotional nuance introduces considerations that extend beyond informational content.

Despite this, users do not frequently ask whether AI-generated responses are appropriate substitutes for human engagement in such contexts. The system's ability to produce a coherent response is often taken as sufficient. The distinction between simulation and lived experience remains implicit within the interaction, rather than being examined through explicit questioning.

This dynamic reflects a broader tendency to equate capability with suitability. When a system can perform a function, it is often assumed that the function can be applied. The survey material indicates that the boundary between these two dimensions is not consistently explored. Questions that would examine the appropriateness of AI use in specific contexts are less frequently observed.

Another aspect of boundary-related absence is the limited exploration of accountability. When AI-generated outputs are integrated into decisions or actions, questions arise regarding responsibility—who is accountable for the outcome, how the decision is justified, and how errors are addressed. The survey responses suggest that these questions are not commonly foregrounded within AI interactions.

Instead, the system is positioned as a contributor to the task, and its output is treated as part of the decision-making process. The boundary between system-generated input and human responsibility remains implicit. This does not necessarily result in ambiguity in every instance, but it reduces the visibility of how responsibility is distributed within the interaction.

The absence of explicit accountability considerations can be understood as part of the broader transactional model. When the interaction is framed as a means of obtaining an answer, the focus remains on the output. The processes through which that output is generated, and the implications of using it, are not consistently examined.

The survey material also indicates that users do not frequently engage with domain-specific boundaries. Different domains impose different constraints on how information can be interpreted and applied. Legal, medical, and organisational contexts, for example, may require adherence to specific standards or practices. However, interactions with AI systems often occur at a general level, without explicit consideration of how these domain constraints influence the use of the output.

This generalisation contributes to a form of boundary ambiguity. The output may be accurate in a general sense, but its applicability within a specific domain may depend on factors that are not captured within the response. The absence of questions that address these factors means that the boundary between general knowledge and domain-specific application remains unexamined.

Another dimension of this pattern is the limited exploration of dependency. As AI systems are integrated into workflows, they can influence how tasks are performed and how decisions are made. The survey responses suggest that users do not consistently examine how reliance on AI may shape their own capabilities, processes, or structures over time. Questions related to dependency, adaptation, or shifts in responsibility are not commonly observed within individual interactions.

This absence aligns with the underdevelopment of meta-learning identified in Chapter 8. Without examining how interaction patterns evolve, the boundaries of use remain defined by immediate functionality rather than by longer-term considerations. The system is used as it is encountered, without systematic reflection on how that use may change over time.

The cumulative effect of these dynamics is the emergence of a stable interaction pattern in which boundaries are present but not explicitly articulated. The system is used across a wide range of contexts, but the conditions that define appropriate use are not consistently examined through structured questioning.

This absence does not imply that users are unaware of limitations or risks. Rather, it reflects how such considerations are integrated into the interaction. The survey material suggests that awareness does not always translate into explicit inquiry. Boundaries remain implicit, and the interaction proceeds without systematically surfacing them.

The significance of this pattern lies in its connection to the broader structure of AI use. Boundaries define the limits within which outputs can be interpreted and applied. When these limits are not examined, the interaction remains focused on capability and output, without fully engaging with the context in which those outputs operate.

This chapter identifies the absence of boundary-oriented questioning as a distinct category of unasked questions. It highlights how the focus on what AI can do can overshadow the examination of where its use may be limited, inappropriate, or contextually constrained.

By making this absence visible, it becomes possible to examine how boundaries interact with other structural elements identified in this Guide, including evaluation, adversarial thinking, and second-order reasoning. Together, these patterns contribute to a more comprehensive understanding of how AI systems are currently engaged and what dimensions of that engagement remain underdeveloped.

Chapter 10 — Structural Causes of the Gaps: Habit, Incentives, and Cognitive Bias

Across the preceding chapters, a consistent set of absences has been identified: the absence of evaluation, the absence of self-interrogation, the avoidance of adversarial thinking, the underdevelopment of second-order reasoning, the limited engagement with meta-learning, and the lack of explicit boundary-oriented questioning. These absences do not appear as isolated phenomena. They form a coherent pattern across interactions, suggesting that they are not random omissions but the result of underlying structural forces.

This chapter examines those underlying forces. Rather than attributing the gaps to individual oversight or system limitations, the survey material indicates that they are shaped by the interaction of three primary factors: habit, incentives, and cognitive bias. These factors operate in combination to define how AI systems are engaged, what forms of inquiry are prioritised, and which remain underrepresented.

The first of these factors is habit. Human interaction with information systems has been shaped over decades by tools that emphasise retrieval, execution, and efficiency. Search engines, databases, and productivity software have conditioned users to frame queries in ways that produce direct and actionable outputs. This conditioning is not superficial; it forms a deeply embedded pattern of engagement.

When users approach AI systems, they do not do so in a conceptual vacuum. They carry forward these established habits. Questions are framed in ways that resemble search queries or task instructions. The objective is to obtain a useful output with minimal iteration. This habitual framing influences not only the content of the query, but the expectations surrounding the interaction.

The survey responses indicate that these habits persist even when the capabilities of AI systems extend beyond those of earlier tools. AI systems can engage in iterative reasoning, examine assumptions, and explore alternative perspectives. However, these capabilities are not automatically activated. The interaction is shaped by the habits that users bring into it. As a result, the system is engaged within a familiar paradigm, and its broader capabilities remain underutilised.

Habit also contributes to the stability of interaction patterns over time. Once a particular mode of engagement proves effective—producing coherent outputs and supporting task completion—it is reinforced. Users are less likely to deviate from patterns that yield consistent results. This reinforcement reduces the likelihood of experimenting with alternative forms of inquiry, particularly those that introduce complexity or uncertainty.

The second structural factor is incentives. The environments in which AI systems are used often prioritise speed, efficiency, and visible output. In professional contexts, productivity is frequently measured by the ability to produce results—reports, analyses, decisions—within defined timeframes. In such environments, interactions that generate immediate outputs are aligned with prevailing incentives.

The survey material suggests that these incentives shape how AI systems are used. Questions are framed to produce outputs that can be directly applied or shared. The interaction is evaluated based on its contribution to observable outcomes. In contrast, forms of inquiry that do not produce immediate outputs—such as examining assumptions, exploring uncertainty, or engaging in adversarial thinking—are less directly aligned with these incentives.

This alignment influences the frequency with which different types of questions are asked. Output-oriented queries are reinforced because they produce tangible results that align with external expectations. Inward-facing or exploratory queries, which may require additional time and may not yield immediate outputs, are less frequently prioritised.

Incentives also operate at the level of perceived value. The immediate utility of an output is often more visible than the longer-term value of deeper inquiry. For example, generating a report or summary provides a clear and immediate benefit. In contrast, examining the assumptions underlying that report or exploring its potential limitations may not produce a tangible output that can be directly evaluated.

The survey responses indicate that this disparity in perceived value contributes to the underrepresentation of certain forms of inquiry. The interaction remains focused on what can be measured and demonstrated, rather than on processes that operate at a more abstract level.

The third structural factor is cognitive bias. Human reasoning is shaped by a range of biases that influence how information is processed, how decisions are made, and how uncertainty is handled. These biases are not unique to AI interaction, but they play a significant role in shaping how AI systems are engaged.

One of the most relevant biases in this context is confirmation bias—the tendency to seek information that supports existing beliefs or assumptions. The survey material suggests that users often frame questions in ways that align with their existing perspective. AI systems, when presented with such questions, generate responses that fit within that frame. This creates a reinforcing loop in which the user's perspective is elaborated rather than challenged.

Another relevant bias is the preference for cognitive ease. Humans tend to favour interactions that are clear, straightforward, and require minimal effort to process. AI-generated outputs are often designed to be fluent and coherent, aligning with this preference. As a result, responses that appear complete and well-structured are more likely to be accepted without further interrogation.

This preference for cognitive ease interacts with the avoidance of friction identified in earlier chapters. Questions that introduce complexity—such as those involving uncertainty, failure conditions, or adversarial perspectives—require additional cognitive effort. The survey responses indicate that such questions are less frequently asked, as they do not align with the preference for simplicity and clarity.

Another cognitive factor is overconfidence in one's ability to detect errors or limitations. Users may assume that they will recognise when an output is incorrect or incomplete. This assumption reduces the perceived need to explicitly examine uncertainty or failure conditions. The interaction proceeds on the basis that any significant issues will be apparent.

The survey material suggests that this assumption is not always tested within the interaction. Questions that would explicitly probe the limits of the output—asking under what conditions it might fail or what information might be missing—are not consistently observed. The reliance on implicit judgment reduces the likelihood of engaging with these dimensions.

These cognitive biases do not operate independently of habit and incentives. They interact with them to reinforce existing patterns of interaction. For example, the preference for cognitive ease aligns with incentives for efficiency, while confirmation bias aligns with habitual framing of questions. Together, these factors create a stable environment in which certain forms of inquiry are consistently prioritised and others remain underrepresented.

It is also important to note that these structural causes are not inherently problematic. Habits enable efficient interaction, incentives drive productivity, and cognitive biases support decision-making in complex environments. The survey material does not indicate that these factors should be eliminated. Rather, it highlights how they shape the structure of AI interaction.

The gaps identified in previous chapters can therefore be understood as the outcome of these structural influences. The absence of evaluation reflects the prioritisation of outputs over processes. The avoidance of adversarial thinking reflects the preference for cognitive ease and alignment. The underdevelopment of meta-learning reflects the focus on immediate tasks rather than on cumulative understanding.

Similarly, the absence of boundary-oriented questioning reflects the assumption that capability implies appropriateness, an assumption reinforced by both habit and incentives. The lack of second-order thinking reflects the emphasis on immediate outcomes rather than on extended consequences, an emphasis aligned with efficiency and clarity.

These patterns are not imposed by AI systems. They emerge from the interaction between human tendencies and the structural context in which AI is used. The system responds to the questions it is given, within the structure those questions define and the questions are shaped by these underlying factors.

The significance of identifying these structural causes lies in understanding the coherence of the observed gaps. The absences are not random; they are the predictable result of how interaction is structured. This understanding provides a foundation for examining the implications of these patterns, which will be explored in the following chapters.

By situating the gaps within the context of habit, incentives, and cognitive bias, this chapter connects the observed patterns of interaction to broader behavioural and structural dynamics. It shows that the absence of certain forms of inquiry is not simply a matter of oversight, but a reflection of how human–AI interaction is currently organised.

The chapters that follow will extend this analysis by examining the implications of these patterns over time, particularly in relation to decision-making, capability development, and the differentiation of outcomes across individuals and organisations.

Chapter 11 — Implications for Individuals and Organisations (3–8 Year Horizon)

Across the preceding chapters, a consistent set of structural patterns has been identified in how AI systems are engaged. These include the prioritisation of outputs over judgment, the absence of evaluation, the limited use of self-interrogation, the avoidance of adversarial thinking, the underdevelopment of second-order reasoning, and the lack of explicit boundary-oriented questioning. These patterns are not isolated behaviours; they form an integrated interaction model shaped by habit, incentives, and cognitive bias.

When considered over a short time horizon, these patterns may not produce immediate or visible consequences. AI systems continue to generate useful outputs, tasks are completed more efficiently, and workflows appear to improve in speed and scale. However, when extended over a medium-term horizon of three to eight years, the implications of these patterns begin to accumulate. These implications are not uniform; they affect individuals and organisations in ways that reflect how these interaction patterns are sustained and embedded.

One of the most immediate implications is the divergence between output production and judgment capability. As AI systems increasingly handle routine cognitive tasks, the production of outputs becomes more accessible and less differentiated. Reports, analyses, summaries, and content can be generated at scale with minimal variation in structure or quality. Within this environment, the distinguishing factor shifts away from output itself toward the capacity to interpret, evaluate, and apply that output.

The survey material suggests that current interaction patterns do not consistently develop this capacity. When outputs are accepted without examination, the processes of judgment remain underutilised. Over time, this can lead to a widening gap between the ability to generate outputs and the ability to critically engage with them. Individuals who rely primarily on AI-generated outputs without engaging in evaluation or adversarial thinking may find that their capacity for independent judgment does not develop at the same pace as their capacity for production.

At an organisational level, this divergence can manifest in decision-making processes. Teams may produce analyses and recommendations more quickly, but the depth of examination underlying those outputs may not increase proportionally. Decisions may be based on information that appears comprehensive but has not been systematically evaluated for assumptions, uncertainty, or failure conditions. This does not necessarily lead to immediate errors, but it can introduce fragility into decision-making structures.

Another implication relates to the accumulation of what can be described as decision debt. When decisions are made based on outputs that have not been fully examined, the underlying assumptions and limitations remain unaddressed. Over time, as conditions change or new information emerges, these unexamined elements can create misalignments between decisions and outcomes. The need to revisit or revise earlier decisions may increase, not because the initial outputs were incorrect, but because their limitations were not fully considered.

This pattern is reinforced by the absence of second-order thinking. Without systematically examining the downstream effects of actions, individuals and organisations may focus on immediate optimisation without fully accounting for longer-term consequences. Actions that appear effective in the short term may introduce complexities or constraints that become visible only over time. The survey material indicates that such temporal extensions are not consistently integrated into AI interactions, contributing to this dynamic.

A further implication is the potential for skill atrophy. As AI systems take on a greater share of cognitive tasks, the need for individuals to perform those tasks independently may decrease. This shift is not inherently negative; it reflects the redistribution of effort within a system that includes both human and AI components. However, when the interaction does not include mechanisms for maintaining or examining underlying capabilities, certain skills may become less frequently exercised.

The survey responses highlight that users do not consistently engage with questions about how their own capabilities are changing as a result of AI use. Without such engagement, changes in skill levels may not be immediately visible. Over time, individuals may become more dependent on AI systems for tasks that were previously performed independently, without a clear understanding of how this dependency affects their overall capability.

At an organisational level, this dynamic can influence the development of talent and expertise. If AI systems are used primarily for output generation without corresponding engagement in evaluation or learning processes, the development of deeper expertise may be affected. New entrants into a field may rely on AI-generated outputs without fully developing the underlying frameworks that support independent reasoning. This can create a structural shift in how expertise is formed and maintained.

The absence of adversarial thinking also has implications for robustness. When ideas and plans are not systematically challenged, their weaknesses may remain unexamined. In stable environments, this may not produce immediate issues. However, in contexts characterised by change or uncertainty, unexamined weaknesses can become more significant. The ability to anticipate and respond to such changes depends in part on the extent to which ideas have been tested against alternative perspectives.

The survey material suggests that current interaction patterns do not consistently incorporate this form of testing. As a result, individuals and organisations may develop strategies or approaches that appear coherent within their initial framing but have not been examined from opposing viewpoints. This can limit the adaptability of those strategies over time.

Another implication relates to trust. As AI systems produce coherent and contextually appropriate outputs, users may develop a level of trust based on repeated positive interactions. This trust is not necessarily problematic, but when it is not accompanied by systematic evaluation, it may be based primarily on surface characteristics of the output. The distinction between plausibility and validity may not be consistently examined.

Over time, this can influence how information is interpreted and applied. Outputs that align with expectations may be accepted without further questioning, while outputs that introduce complexity or uncertainty may be less readily integrated. This dynamic can shape the information environment within which individuals and organisations operate, influencing how decisions are made and how risks are assessed.

The absence of boundary-oriented questioning also has implications for accountability. When the role of AI within a decision-making process is not explicitly examined, the distribution of responsibility remains implicit. This may not be immediately problematic in routine contexts, but in situations where decisions have significant consequences, the lack of clarity regarding boundaries can become more relevant.

The survey responses indicate that users do not consistently engage with questions about where AI use is appropriate or how responsibility is allocated. Over time, this can create ambiguity in how decisions are justified and how outcomes are evaluated. The system contributes to the process, but its role is not explicitly defined within a broader framework of accountability.

At a systemic level, these patterns can contribute to a form of convergence in how AI is used. As similar interaction patterns are adopted across individuals and organisations, the outputs generated by AI systems may become more standardised. The differentiation between users may increasingly depend on how they engage with the outputs—how they interpret, evaluate, and integrate them—rather than on the outputs themselves.

The survey material suggests that current interaction patterns do not consistently emphasise this dimension of engagement. As a result, there may be a divergence between those who engage with AI primarily at the level of output and those who engage with it at the level of reasoning. This divergence is not explicitly articulated within individual interactions, but it may become more visible over time as differences in judgment, adaptability, and decision-making accumulate.

It is also notable that these implications are not deterministic. The patterns identified in this Guide describe tendencies, not fixed outcomes. The extent to which these implications manifest depends on how interaction patterns are sustained, adapted, or varied over time. However, the consistency of the observed patterns suggests that, in the absence of structural variation, similar trajectories may emerge across different contexts.

This chapter has examined the implications of current AI interaction patterns over a medium-term horizon. It has focused on how the absence of certain forms of inquiry—evaluation, adversarial thinking, second-order reasoning, meta-learning, and boundary examination—can shape outcomes for individuals and organisations.

The following chapter will extend this analysis by examining how these patterns interact to create compounded effects, particularly in relation to risk, resilience, and the structure of decision-making systems.

Chapter 12 — Compounding Effects: Risk, Resilience, and Decision Structures

Across the preceding chapters, a series of structural gaps in AI interaction has been identified and examined. These include the prioritisation of outputs over judgment, the absence of evaluation, the limited engagement with self-interrogation, the avoidance of adversarial thinking, the underdevelopment of second-order reasoning, the lack of meta-learning, and the absence of explicit boundary-oriented questioning. Each of these patterns has been described individually. However, their significance becomes more pronounced when considered in combination.

This chapter examines how these patterns interact to produce compounding effects over time. Rather than operating in isolation, the identified gaps reinforce one another, shaping how risk is perceived, how resilience is developed, and how decision structures evolve within individuals and organisations. The interaction of these elements creates systemic dynamics that extend beyond the immediate context of any single AI interaction.

One of the central features of these compounding effects is the amplification of risk through alignment of gaps. When multiple forms of inquiry are absent simultaneously—evaluation, adversarial thinking, and second-order reasoning, for example—the interaction environment becomes increasingly oriented toward surface-level coherence. Outputs are generated, accepted, and applied without systematic examination of their underlying assumptions or potential limitations.

This alignment does not necessarily result in immediate failure. In many cases, the outputs remain sufficiently accurate or useful within their immediate context. However, the absence of multiple layers of examination reduces the system's ability to detect and correct errors before they propagate. Small misalignments—such as incomplete assumptions or unexamined dependencies—can accumulate over time, particularly when decisions are built upon previous outputs.

The survey material suggests that users do not consistently revisit prior outputs with a structured lens of evaluation or adversarial scrutiny. As a result, earlier decisions or interpretations may persist without re-examination, even as conditions change. This creates a form of cumulative exposure, where the effects of unexamined elements are not immediately visible but become more significant as they interact with subsequent decisions.

This dynamic is closely related to the concept of resilience. Resilience, in this context, refers to the capacity of individuals and organisations to adapt to change, absorb disruptions, and maintain functionality under varying conditions. The development of resilience depends in part on the ability to anticipate, identify, and respond to potential points of failure.

The patterns identified in earlier chapters suggest that current AI interaction models do not consistently support this capacity. The absence of adversarial thinking limits the identification of weaknesses, while the absence of second-order reasoning reduces visibility into how those weaknesses may evolve over time. The missing layer of evaluation further constrains the ability to assess uncertainty and variability within outputs.

As a result, resilience may not be actively developed through interaction with AI systems. Instead, the interaction remains oriented toward efficiency and output generation. This orientation can be effective in stable environments, where conditions are predictable and deviations are limited. However, in environments characterised by change or complexity, the lack of engagement with risk and variability can reduce the system's adaptive capacity.

Another dimension of compounding effects is the reinforcement of dependency structures. As AI systems are used to generate outputs across a range of tasks, they become integrated into decision-making processes. This integration is not inherently problematic; it reflects the functional role of AI within contemporary workflows. However, when the interaction does not include mechanisms for examining dependency—such as meta-learning or boundary-oriented questioning—the nature of that dependency remains implicit.

The survey material indicates that users do not consistently engage with questions about how reliance on AI systems shapes their own capabilities or processes. Without such engagement, dependency can develop without explicit recognition of its scope or implications. Over time, this can influence how decisions are made, how tasks are structured, and how responsibilities are distributed.

This dynamic interacts with the previously identified pattern of skill atrophy. When tasks are consistently delegated to AI systems without corresponding engagement in underlying reasoning processes, certain capabilities may become less frequently exercised. This does not necessarily result in immediate loss of competence, but it can alter the balance between human and system contributions within a decision structure.

At an organisational level, this shift can influence how expertise is distributed. If AI systems are used primarily for output generation, the role of human judgment may become concentrated in fewer areas. The broader base of individuals engaging in evaluation, adversarial thinking, or second-order reasoning may not expand at the same rate as the use of AI for production. This can create asymmetries within decision structures, where output generation is widely distributed but deeper reasoning remains more limited.

The compounding nature of these effects is also evident in how decision structures evolve. Decision-making processes are often iterative, with each stage building upon previous outputs. When earlier stages are not systematically examined, their limitations can propagate into later stages. The absence of evaluation or adversarial scrutiny at one point in the process can influence the quality of subsequent decisions.

This propagation is not necessarily linear. The interaction of multiple unexamined elements can produce outcomes that are difficult to trace back to a single source. The survey material suggests that users do not consistently engage in tracing the origins of outputs or examining how earlier assumptions influence current conclusions. As a result, the structure of decision-making becomes less transparent.

Another aspect of compounding effects is the convergence of interaction patterns. As similar habits, incentives, and cognitive biases shape AI use across different contexts, the resulting patterns of interaction may become increasingly standardised. Outputs generated by AI systems may exhibit consistent structures and styles, and the processes through which they are interpreted may follow similar trajectories.

This convergence can reduce variation in how problems are approached and how solutions are developed. While standardisation can enhance efficiency, it can also limit the exploration of alternative perspectives. The absence of adversarial thinking and second-order reasoning contributes to this effect, as fewer mechanisms are present to introduce divergence within the interaction.

The survey material indicates that this convergence is not explicitly recognised within individual interactions. Each exchange appears contextually appropriate, and the outputs meet immediate needs. However, when considered collectively, the similarity of interaction patterns becomes more apparent. This similarity can influence how risks are perceived and managed, as well as how opportunities for differentiation are identified.

The interaction of these factors also shapes how uncertainty is experienced. When evaluation and uncertainty analysis are not consistently engaged, outputs may be perceived as more definitive than they are. This perception can influence decision-making, particularly in contexts where uncertainty is inherent. The absence of explicit engagement with uncertainty does not eliminate it; it changes how it is perceived and managed.

Over time, this can lead to a misalignment between perceived and actual certainty. Decisions may be made with a level of confidence that is not fully supported by the underlying information. This does not necessarily result in immediate negative outcomes, but it can affect how individuals and organisations respond when unexpected conditions arise.

The cumulative nature of these dynamics underscores the importance of examining interaction patterns as systems rather than as isolated events. Each individual interaction may appear effective, but the aggregation of patterns over time produces effects that are not visible at the level of a single exchange.

This chapter has focused on how the identified gaps interact to shape risk, resilience, and decision structures. It has highlighted how the absence of certain forms of inquiry can compound over time, influencing not only individual decisions but the broader systems within which those decisions are made.

The following chapter will extend this analysis by examining how these compounding effects contribute to divergence in outcomes, particularly in relation to how different individuals and organisations engage with AI systems and develop their interaction models.

Chapter 13 — Divergence Paths: Output Users vs. Judgment Builders

Across the preceding chapters, a set of consistent interaction patterns has been identified: a focus on output generation, the absence of systematic evaluation, limited engagement with self-interrogation, avoidance of adversarial thinking, underdevelopment of second-order reasoning, minimal meta-learning, and an implicit treatment of boundaries. These patterns, shaped by habit, incentives, and cognitive bias, do not produce uniform outcomes over time. Instead, they give rise to divergence in how individuals and organisations engage with AI systems and how value is derived from those interactions.

This divergence does not emerge as a binary separation, but as a gradual differentiation in interaction models. At one end of this spectrum are users whose engagement with AI remains predominantly oriented toward outputs. At the other end are users whose engagement extends into the development and application of judgment. These categories—output users and judgment builders—are not fixed identities, but represent patterns of interaction that can be observed across contexts.

Output-oriented interaction is characterised by a consistent emphasis on obtaining results. AI systems are engaged to generate answers, produce content, and support task completion. The interaction is efficient, transactional, and aligned with immediate objectives. The patterns identified in earlier chapters—such as the prioritisation of clarity, the acceptance of coherent outputs, and the avoidance of friction—are most visible within this mode of engagement.

Within this pattern, the system functions as a highly capable production mechanism. Outputs are generated at scale, and the user's role is to initiate queries and apply the results. The interaction remains within the boundaries of execution, with limited extension into the examination of how those outputs are formed or how they should be interpreted.

Judgment-oriented interaction, by contrast, extends beyond output generation into the processes of evaluation, interpretation, and synthesis. In this mode, the system is not only a source of answers, but a medium through which reasoning is examined. Questions may engage with uncertainty, explore alternative perspectives, or consider the implications of different courses of action. The interaction becomes iterative, with outputs serving as inputs for further inquiry.

The survey material indicates that both patterns are present, but not equally distributed. Output-oriented interaction is more common, reflecting the structural factors described in Chapter 10. Judgment-oriented interaction appears less frequently, often emerging in contexts where users engage with the system beyond immediate task completion.

The divergence between these patterns is not immediately visible at the level of individual interactions. In many cases, both modes produce outputs that appear similar in form and quality. A report generated through output-oriented interaction may resemble one developed through a more judgment-oriented process. The distinction lies not in the output itself, but in the processes that underpin it.

Over time, however, differences in these processes begin to accumulate. Output users tend to operate within established frames of inquiry. Their interactions are efficient and consistent, but they may not extend into areas that require examination of assumptions, exploration of uncertainty, or consideration of alternative perspectives. The outputs generated are aligned with the initial framing of the question, and the interaction concludes once the output is deemed sufficient.

Judgment builders, in contrast, engage with the interaction at multiple levels. They may examine how a question is framed, how an output is constructed, and how it might change under different conditions. The interaction is not limited to obtaining an answer; it includes the examination of the reasoning process itself. This does not necessarily produce different outputs in every instance, but it introduces variation in how those outputs are interpreted and applied.

The implications of this divergence become more apparent when considered over time. As AI systems increasingly standardise the production of outputs, the differentiation between users shifts toward how those outputs are engaged. Output users may produce results that are consistent with broader patterns, reflecting the capabilities of the system and the prevailing interaction model. Judgment builders may produce results that incorporate additional layers of reasoning, reflecting a more extended engagement with the system.

This divergence is also reflected in how uncertainty is handled. Output-oriented interaction tends to treat outputs as sufficiently complete for immediate application. Uncertainty, when present, may not be explicitly examined. In judgment-oriented interaction, uncertainty becomes a dimension of inquiry. Outputs are considered in relation to their limitations, and the interaction may extend into examining conditions under which those outputs may change.

The survey material suggests that these differences are not always conscious. Users may not explicitly identify themselves as operating within one pattern or another. Instead, the divergence emerges through repeated interaction. The cumulative effect of how questions are framed, how outputs are evaluated, and how interactions are extended shapes the overall pattern.

Another dimension of divergence relates to adaptability. In contexts where conditions remain stable, both interaction patterns may produce similar outcomes. However, in environments characterised by change or complexity, differences in engagement become more pronounced. Output users, operating within established frames, may rely on patterns that have previously produced effective results. Judgment builders, engaging with multiple layers of reasoning, may incorporate a broader range of considerations into their interactions.

This does not imply that one pattern consistently produces superior outcomes. The survey material does not support a deterministic conclusion of that nature. Instead, it indicates that the patterns lead to different modes of engagement, each with its own characteristics and implications. The divergence lies in how interaction is structured and sustained, rather than in a simple hierarchy of effectiveness.

At an organisational level, these patterns can influence how teams and systems are structured. Organisations that primarily engage with AI at the level of output generation may develop processes that emphasise efficiency and scale. The system becomes integrated into workflows as a production tool, and the interaction model remains aligned with this function.

Organisations that engage with AI at the level of judgment may incorporate additional layers into their processes. Interactions may include stages of evaluation, exploration of alternatives, and examination of assumptions. This does not necessarily slow down the process, but it introduces variation in how outputs are generated and interpreted.

The survey responses indicate that these organisational patterns are not always explicitly defined. They emerge from the aggregation of individual interaction models. As individuals engage with AI systems in different ways, these patterns influence the broader structure of organisational processes.

The divergence between output users and judgment builders also interacts with the development of expertise. Output-oriented interaction supports the efficient generation of results, but may not consistently engage the processes through which deeper understanding is developed. Judgment-oriented interaction, by engaging with evaluation and reasoning, may contribute to the development of frameworks that can be applied across contexts.

Over time, this can influence how expertise is distributed. Individuals who engage with AI at the level of judgment may develop a different relationship with the system, using it not only as a source of outputs but as a medium for examining and refining their thinking. Those who engage primarily at the level of output may rely more heavily on the system for production, with less emphasis on the underlying processes.

The survey material suggests that this divergence is likely to become more visible as AI systems become more integrated into everyday workflows. As the production of outputs becomes increasingly standardised, the differences in how those outputs are engaged may become a more significant factor in shaping outcomes.

It is important to note that this divergence is not fixed or predetermined. Users may move between these patterns depending on context, task, or experience. The categories of output users and judgment builders are not rigid classifications, but descriptive constructs that capture observable tendencies within interaction.

This chapter has described how divergence emerges from the interaction patterns identified in earlier chapters. It has focused on how differences in engagement—particularly in relation to evaluation, adversarial thinking, and meta-learning—can lead to distinct modes of interaction over time.

The final chapter will synthesise these patterns, bringing together the structural elements identified throughout this Guide to provide a cohesive understanding of how the absence of certain questions shapes AI use without prescribing a particular mode of engagement.

Chapter 14 — Synthesis: Reframing AI Use Without Prescription

Across the preceding chapters, a consistent set of patterns has been identified in how AI systems are engaged. These patterns are not defined by technical limitations, nor by isolated user behaviours. They emerge from the structure of interaction itself—how questions are framed, how outputs are interpreted, and which dimensions of inquiry are consistently included or excluded.

The central organising concept of this Guide has been absence. Not the absence of capability, but the absence of certain types of questions. These absences are not random. They are structured, recurring, and observable across multiple systems and contexts. They form a coherent pattern that shapes the overall nature of AI use.

This synthesis does not introduce new categories or extend beyond the established structure. Instead, it brings together the identified elements—absence of evaluation, absence of self-interrogation, avoidance of adversarial thinking, underdevelopment of second-order reasoning, limited meta-learning, and implicit treatment of boundaries—into a single frame of understanding.

At the core of this frame is the distinction between interaction as execution and interaction as examination. The surveyed responses indicate that AI is predominantly engaged within an execution-oriented model. Questions are framed to produce outputs, and the interaction concludes once those outputs meet a threshold of usefulness. This model is efficient, scalable, and aligned with established habits and incentives.

Within this model, the system functions as a production mechanism. It generates responses that are coherent, structured, and contextually relevant. The interaction is defined by its ability to produce results. This orientation is reinforced by the characteristics of the outputs themselves, which are presented in a manner that suggests completeness and resolution.

However, the execution model does not inherently engage the processes that surround output generation. It does not consistently activate evaluation, does not require examination of assumptions, and does not extend into the exploration of consequences. These dimensions remain peripheral, not because they are inaccessible, but because they are not structurally embedded in the dominant interaction pattern.

The absence of evaluation, as described in Chapter 4, illustrates this dynamic. Outputs are generated and accepted without systematic engagement with uncertainty or failure conditions. The interaction remains at the level of what is produced, rather than how it should be interpreted. This absence does not prevent the use of outputs, but it shapes the conditions under which they are applied.

Similarly, the absence of self-interrogation, examined in Chapter 5, reflects the outward orientation of inquiry. Questions are directed toward problems and tasks, while the framing of those problems remains unexamined. The system responds to the structure provided, and the user's perspective is reinforced rather than questioned. The interaction proceeds without extending into the examination of the user's own reasoning processes.

The avoidance of adversarial thinking, explored in Chapter 6, further reinforces this pattern. Interactions are aligned with the user's initial direction, and alternative or opposing perspectives are not systematically introduced. The absence of challenge contributes to a form of coherence that is not necessarily accompanied by robustness. The output appears consistent, but its capacity to withstand critique is not always examined.

The absence of second-order thinking, described in Chapter 7, limits the temporal dimension of interaction. Questions are framed at the level of immediate outcomes, and the exploration of downstream effects remains underdeveloped. The interaction concludes once the first-order objective is achieved, without extending into how the situation may evolve.

The underdevelopment of meta-learning, examined in Chapter 8, reflects the lack of cumulative engagement. Each interaction is treated as discrete, and the process of interacting with AI is not itself examined. Patterns of use are reinforced over time, but not systematically analysed. The interaction remains focused on content, rather than on the process through which that content is generated and interpreted.

The absence of boundary-oriented questioning, described in Chapter 9, highlights how the limits of AI use remain implicit. The system is engaged based on capability, and the question of appropriateness is not consistently foregrounded. The distinction between what can be done and what should be done is not structurally embedded in the interaction.

Chapter 10 situates these absences within the broader context of habit, incentives, and cognitive bias. These structural factors explain why the observed patterns are stable and recurring. Habits shape how questions are framed, incentives prioritise outputs, and cognitive biases influence how information is processed. Together, they create an interaction environment in which certain forms of inquiry are consistently prioritised and others remain underrepresented.

The implications of these patterns, examined in Chapter 11, extend beyond individual interactions. Over time, the absence of deeper forms of inquiry influences how judgment is developed, how decisions are made, and how outputs are interpreted. The interaction model shapes not only what is produced, but how it is used.

Chapter 12 expands this perspective by examining how these patterns interact to produce compounding effects. The absence of multiple layers of inquiry—evaluation, adversarial thinking, and second-order reasoning—creates an environment in which small misalignments can accumulate. Risk, resilience, and decision structures are shaped by how these gaps reinforce one another over time.

Chapter 13 introduces the concept of divergence, illustrating how different patterns of engagement lead to different trajectories. Output-oriented interaction and judgment-oriented interaction represent two ends of a spectrum. The divergence between them is not immediate, but emerges through repeated interaction. It reflects how individuals and organisations engage with AI systems over time.

This synthesis brings these elements together into a cohesive frame. It does not prioritise one pattern over another, nor does it prescribe a particular mode of engagement. Instead, it describes the structure within which AI use currently operates. The absence of certain questions defines the boundaries of that structure.

Within this frame, AI systems can be understood as operating across two dimensions simultaneously. On one dimension, they function as tools for execution, producing outputs that support tasks and workflows. On another dimension, they function as environments for reasoning, capable of supporting exploration, evaluation, and reflection. The surveyed responses indicate that the first dimension is dominant, while the second remains underutilised.

This imbalance is not static. It reflects the current state of interaction, shaped by the factors described throughout this Guide. The structure of use is not determined solely by the system, but by how the system is engaged. The absence of certain questions is therefore not a limitation imposed by technology, but a feature of interaction.

By framing these absences explicitly, this Guide has sought to make visible a dimension of AI use that is often implicit. The patterns identified are not prescriptive conclusions, but observational insights derived from cross-system analysis. They reflect how AI systems are currently integrated into human thinking processes, and how certain forms of inquiry remain outside the dominant model.

The significance of this synthesis lies in its ability to connect individual observations into a coherent whole. Each chapter has examined a specific aspect of absence, but the interaction of these aspects defines the broader structure. The absence of evaluation reinforces the output bias. The avoidance of adversarial thinking supports the narrowing of inquiry. The lack of meta-learning stabilises existing patterns. Together, these elements form an integrated system of interaction.

This system is characterised by efficiency, coherence, and scalability. It supports the rapid generation of outputs and the execution of tasks. At the same time, it leaves certain dimensions of inquiry underexplored. These dimensions—evaluation, self-interrogation, adversarial thinking, second-order reasoning, and boundary examination—exist within the system, but are not consistently activated.

This synthesis does not resolve these patterns or propose a transformation. It maintains the observational stance established throughout the Guide. The purpose is not to prescribe how AI should be used, but to describe how it is currently being used, and what remains outside that use.

In doing so, it provides a structured understanding of the interaction between human reasoning and AI systems. It highlights the role of absence as a defining feature of that interaction, and it situates that absence within a broader context of habit, incentives, and cognitive bias.

The Guide concludes not with a directive, but with a reframing. AI use, as observed across systems, is not only defined by what is asked, but by what is not. The structure of interaction is shaped as much by omission as by inclusion. Recognising this structure provides a lens through which AI use can be understood, without prescribing how it should evolve.

Future Edition Updates & User Submissions

AISF publications are designed to evolve in alignment with developments in artificial intelligence and its real-world usage.

Future editions of this Guide may incorporate:

• updated cross-system observations
• additional patterns of interaction
• refined analytical frameworks
• expanded coverage of emerging use cases

AISF may also consider structured user submissions where they contribute to the clarity, neutrality, and analytical integrity of future editions.

All updates and submissions are subject to AISF's editorial and governance standards to ensure consistency, neutrality, and institutional quality.

Acknowledgements

This Guide reflects a cross-system synthesis of interactions with multiple AI systems.

AISF acknowledges the role of these systems in enabling comparative analysis and structured observation of emerging patterns in AI use.

The development of this Guide is informed by AISF’s broader research methodology, which emphasises neutrality, multi-system validation, and disciplined analytical framing.

About

AI Sourced Facts (AISF) Pte. Ltd.

AISF is a Singapore-headquartered institution dedicated to structured reasoning, responsible AI navigation, and governance-informed adoption of artificial intelligence systems.

AISF operates with a capability-first, vendor-neutral posture. Its publications do not rank platforms, endorse providers, or promote specific technologies. Instead, AISF develops structured frameworks that help individuals, professionals, and institutions reason clearly before integrating AI into operational, strategic, or educational environments.

AISF's work spans whitepapers, applied insight books, education instruments, governance architectures, and structured research initiatives. These outputs are informed by cross-system AI research methodologies and reflect globally observed usage patterns at the time of publication. Human accountability remains central across all AISF frameworks.

AISF does not provide regulatory, legal, financial, investment, or compliance advice. Its publications are designed to support structured thinking, proportionate governance, and disciplined evaluation of AI capabilities prior to deployment or reliance.

As artificial intelligence systems continue to evolve, AISF's focus remains constant: clarity before integration, governance proportionate to capability, and long-term institutional resilience in the age of AI.

Back Cover

AI Use — What People Are Not Asking (And Why It Matters)

Most discussions about artificial intelligence focus on what people are asking—and what AI systems can deliver in response.

This Guide takes a different approach.

It examines what is *not* being asked.

Across multiple AI systems and contexts, consistent patterns emerge—not in the presence of questions, but in their absence. Questions relating to evaluation, assumptions, consequences, and boundaries are often underrepresented. These omissions are not random. They reflect how AI is currently integrated into human thinking.

This Guide presents a structured, cross-system analysis of these gaps. It explores how interaction patterns are shaped by habit, incentives, and cognitive bias, and how these patterns influence judgment, decision-making, and long-term capability development.

It does not prescribe how AI should be used.

It provides a framework for understanding how it is being used—and what remains outside that use.