AI Awareness

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Abstract

Recent breakthroughs in artificial intelligence (AI) have brought about increasingly capable systems that demonstrate remarkable abilities in reasoning, language understanding, and problem-solving. These advancements have prompted a renewed examination of **AI awareness**—not as a philosophical question of consciousness, but as a measurable, functional capacity. In this review, we explore the emerging landscape of AI awareness, which includes meta-cognition (the ability to represent and reason about its own state), self-awareness (recognizing its own identity, knowledge, limitations, *inter alia*), social awareness (modeling the knowledge, intentions, and behaviors of other agents), and situational awareness (assessing and responding to the context in which it operates).

First, we draw on insights from cognitive science, psychology, and computational theory to trace the theoretical foundations of awareness and examine how the four distinct forms of AI awareness manifest in state-of-the-art AI. Next, we systematically analyze current evaluation methods and empirical findings to better understand these manifestations. Building on this, we explore how AI awareness is closely linked to AI capabilities, demonstrating that more aware AI agents tend to exhibit higher levels of intelligent behaviors. Finally, we discuss the risks associated with AI awareness, including key topics in AI safety, alignment, and broader ethical concerns.

AI awareness is a double-edged sword: it improves general capabilities, *i.e.*, reasoning, safety, while also raises concerns around misalignment and societal risks,

demanding careful oversight as AI capabilities grow. On the whole, our interdisciplinary review provides a roadmap for future research and aims to clarify the role of AI awareness in the ongoing development of intelligent machines.

Keywords: Artificial Intelligence, Awareness, Large Language Model, Cognitive Science, AI Safety and Alignment

1 Introduction

Recently, the rapid acceleration of large language model (LLM) development has transformed artificial intelligence (AI) from a narrow, task-specific paradigm into a general-purpose intelligence with far-reaching implications. Contemporary LLMs demonstrate increasingly sophisticated linguistic, reasoning, and problem-solving capabilities, and are showcasing superb human-like behaviors, prompting a fundamental research question:

To what extent do these systems exhibit forms of awareness?

We want to note here, while the notion of AI consciousness remains both philosophically contentious and empirically less grounded, the concept of AI awareness — defined as a system's functional ability to represent and reason about its own identity, capabilities, and informational states — has emerged as an important and tractable research frontier.

The theoretical foundations of awareness are deeply rooted in cognitive science and psychology, where awareness is typically classified into perceptual awareness, self-awareness, and social awareness. In these fields, awareness is understood as the ability to access and monitor mental states, reason about them, and adjust behavior accordingly. Recent work in computational cognitive science suggests that certain aspects of awareness may be approximated by large-scale generative models that exhibit metacognitive behaviors, calibrate their epistemic confidence, and engage in perspective-taking. These functional abilities raise pressing questions about how awareness manifests in LLMs, how it can be systematically measured, and what implications it holds for AI capability, safety and alignment.

Despite the increasing attention devoted to this topic, the study of AI awareness remains fragmented across disciplines, with limited consensus regarding its definition, measurement, and significance. Some scholars emphasize emergent capabilities observed through prompt-based introspection or theory-of-mind-inspired tests; others caution against anthropomorphizing statistical models, warning that apparent self-reflection may arise from linguistic pattern completion rather than genuine metacognitive representation. Moreover, current methodologies for assessing AI awareness are often limited by confounding factors such as prompt sensitivity, dataset leakage, and lack of longitudinal robustness.

This review provides the first comprehensive, cross-disciplinary synthesis of AI awareness research. We begin by laying out the theoretical foundations, carefully

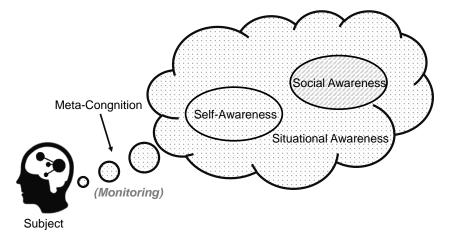


Fig. 1: Four dimensions of "main" awareness. Meta-cognition monitors the subject's own processes and gives rise to self-awareness, social awareness of other individuals and the social collective, and situational awareness of the non-agent environment.

distinguishing AI awareness from AI consciousness, and examining how awareness-related concepts have been formalized in cognitive and computational sciences. Next, we critically evaluate experimental approaches for testing LLM awareness, highlighting both their empirical findings and methodological limitations. We then explore the potential beneficial relationships between functional AI awareness and AI capabilities, from improving model reasoning and task planning to enhancing AI safety. Finally, we address the emerging risks associated with more aware AI systems, focusing on key concerns within the safety and alignment community—such as risks of deception, manipulation, and emergent behaviors that challenge controllability—and broader ethical issues, including concerns like false anthropomorphization.

By integrating insights from AI, cognitive science, psychology, AI safety and alignment, this review not only provides a structured and authoritative account of the current state of knowledge but also charts a roadmap for future inquiry. In doing so, it seeks to advance understanding of one of the most profound and interdisciplinary challenges at the intersection of AI, cognition science and our society.

2 Theoretical Foundations of AI Awareness

In this section, we will review the approaches, goals, and theories of AI consciousness that have emerged with large language models, distinguish between the research subjects that caused linguistic confusion, and clarify the targets of awareness research. In the psychology encyclopedia, awareness represents the perception or knowledge of something. When an agent possesses a "knowledge and knowing state about an internal/external situation or fact," it gains awareness of its target of knowing. Accurate reportability of something perceived or known is widely used as a behavioral index of conscious awareness. However, it is possible to be aware of something without being

explicitly conscious of it [1]. Early works that navigate the range of human awareness [2-5], in which we easily conflate AI awareness with phenomenological consciousness. In animal and human studies, consciousness represents the subjective experience of being in a certain state of mind, and having consciousness means possessing a subjective point of view [5]. Dehaene et al. [6] distinguish between mere global availability of information and true reflective self-consciousness, calling the latter "C2" or selfmonitoring, which entails the system observing its own processing. To prove there is an extra layer of reflective experience, where the AI assesses its own knowledge and decisions, is difficult, if not impossible. Having a conceptual or computational self-model is not the same as having the subjective, qualitative self-awareness that humans have. Since phenomenal observations do not provide sufficient evidence for the existence of consciousness, the "hard problem" of AI consciousness remains scientifically unresolved [5, 7]. Research tends to use a theory-heavy approach to construct hypotheses for the formats of consciousness that ultimately lead to metaphysical discussions. Thus, because of the inconclusivity of metaphysical consciousness, we return to a phenomenological analysis of capacities, behaviors, and observable acquisition of knowledge.

Between 2022 and 2023, there were reports of LLMs performing tasks that required understanding the knowledge and intentions of others, abilities that are central to human social awareness. This has led to questions about whether LLMs are developing rudimentary awareness. However, it is crucial to approach these claims with care and define awareness criteria. Inspired by work in cognitive science, researchers have begun crafting definitions specific to AI. For example, Berglund et al. [8] define situational awareness in an AI context as the model being aware that it's a model and recognizing the difference between training/testing conditions and the real deployment environment. Separately, Chen et al. [9] identify self-cognition (a term closely related to self-awareness) in LLMs as the ability of an LLM to identify its identity as an AI model (beyond just a name or role) and to demonstrate an understanding of itself. These working definitions capture the notion that an LLM with awareness would not just parrot training data blindly—it would have some internal knowledge of its own status or limits.

2.1 Major Types of Awareness Emergence in Modern LLMs Self-awareness

In humans, self-awareness is a hallmark of higher consciousness, representing the ability to become the object of one's own attention and to recognize oneself as separate from others [10]. As early as 1972, Duval and Wicklund [4] proposed that self-awareness states occur when an individual's attention is directed to the self as self-awareness, as opposed to the general awareness of the environment. Self-knowledge is impossible without self-awareness, and having self-awareness benefits introspection, self-regulation, and intensified emotional reactions [11]. The self, as an apparatus that carries an individual's subjective experience, has different levels of competence. Subject's competence to be aware of themselves varies widely among animals or other intelligences who have the ability to process information, think, or give feedback to the environment to some degree, but are not always able to produce content about

themselves [10, 12]. Humans learn about their identities through interacting with society, and thus, knowledge about ourselves also has social attributes and is related to emotional intelligence. Eurich [13] differentiated internal and external self-awareness among humans based on the nature of targets in the society to be aware of. Internal self-awareness represents the ability to understand the impact of one's own emotions, beliefs, states, values, and related factors on decision-making behaviors; external self-awareness represents an individual's ability to identify other individuals' perceptions of them and provide feedback on them.

Self-awareness in artificial intelligence refers to an AI system's capacity to model and understand itself as a distinct entity, including knowledge of its internal states, processes, and its relationship to the external environment. Artificial agents followed the model of humans, yet excluded several sections without strict evidence, such as emotional awareness. It represents a model's capacity to reflect on and understand its own internal states, knowledge boundaries, or behavior patterns, and recognize itself as an entity distinct from others and the environment. The components in AI self-awareness include knowledge about themselves; access to information about their own traits, characteristics, and knowledge boundaries; self-location, introspection, and self-reflection; and the ability to take an objective stance toward it as an agent in the world. Classic demonstrations include robots that can point to themselves in a mirror and AI systems that can correct their mistakes upon introspection.

$Meta ext{-}Cognition$

Meta-cognition was first conceptualized as "the thinking of thinking". [14] conceptualized two core components of meta-cognition: metacognitive knowledge and metacognitive experiences or regulation. In the process of explaining the phenomenological consciousness and a so-called "stage" of being aware, Rosenthal [15] also pointed out the distinction between the disposition of consciousness and the special access we have to our own mental states. Despite the abundance in the definition, with its nature of a reflective process determined, meta-cognition is gradually broken down into components: (1) self-monitoring, (2) self-reflection and probing, and (3) engagement in controlling cognitive processes [16–20]. Proust [19] pointed out that meta-cognition is essentially related to an agent that is always regulating the production and distinction of cognitive processes. An agent probing its own situation constantly asks itself questions like "Am I able to remember this information?" and "Will I use this module in creating the next operation?". A regulatory module of an AI-supported automobile might be supervising its parameters and reflecting its operational status, yet without an agency or a self-probing mechanism, the module continues to run in its original setting without actively interfering, and its self-monitoring will be a result of error reporting rather than cognitive control of the primary cognitive process. In return, reflective behavior indicates at least a stimulation to a more cognitively capable agent in self-monitoring, and modern machines have the capacity to stimulate the monitoring process of reviewing their own cognitive processes. An LLM with meta-cognition can assess its knowledge boundary, evaluate the confidence of its answers, and adjust its reasoning strategy accordingly. Top-tier LLMs can identify which reasoning skills a

task requires [21] and even improve performance via self-reflection and iterative revision of their answers [22, 23]. The model's capacity to "think about its own thinking" by monitoring and regulating its cognitive processes indicates its self-evaluation and correction mechanisms — essentially the model checking its work and refining it [24]. These mechanisms have been shown to boost accuracy in complex problem-solving and code-generation tasks [21, 23]. LLMs often struggle to reliably gauge their own uncertainty or detect when they are wrong.

Situational Awareness

SA represents the perception, comprehension, projection, and prediction of the future of the entities in the environment [25–27]. It was challenging to properly give a conclusive range of situational awareness, as many detailed manifestations differ across psychology, engineering, and systems ergonomics [27–29]. Situational awareness in LLMs typically refers to a model's understanding of its identity and the context in which it is operating. It combines the monitoring of the environment and self-locating knowledge [8, 30, 31]. Primarily, machines and models possess knowledge about facts in the environment, their own influence in the world, and their understanding of how they will be influenced by the world. When utilizing their situational awareness, agents are perceiving the world state and their own state in it in real time. In AI safety literature, this concept is often defined as an LLM being aware that it is a model and recognizing whether it is currently in a testing scenario or deployed in the real world [8]. This form of awareness is critical because a highly capable model that knows it is being evaluated could potentially manipulate its behavior to appear aligned during tests, only to act differently once deployed. Early research has thus focused on measuring and inducing such awareness. Out-of-context reasoning evaluations show that large models can recall details about a test environment from training data (without explicit prompts) to succeed in that environment—an ability that strengthens with model size, hinting at emergent situational awareness as models scale [8]. Laine et al. [30, 31] performed a series of situational awareness tests and verified its importance in enhancing AI functions.

In this article, we distinguish situational awareness from self-awareness in that the content of SA is strictly restricted to sources of information that are not directly related to the agency. From a broader perspective, an agent will naturally know that it is in the scenario modeled by LLM, and this awareness involves both self-understanding and understanding of the environment. The term is so inclusive that it overlaps significantly with self-awareness and social awareness, because any knowledge originates from an environment, and it must be gained through the agent itself. However, given the variety of shapes and purposes of machines and models, there are a number of situations in which we need to make distinctions. Collision avoidance, responsive adaptation to dynamic changes, and accurate state estimation all represent a segment of knowledge of the environment, yet the agents will not possess knowledge about themselves. For example, an autonomous car's awareness is seen in its continuous updating of a world model (other cars, lanes, pedestrians) and predicting future states to avoid. A more cognitive example is an AI security system being aware of the context (it "knows" that the noise it hears is the wind, not an intruder, because it integrates various

sensory cues). With embodiment, sensorimotor awareness of the environment in AI can also include internal senses: a software agent might be "aware" of its CPU usage or memory limit as part of its situational context. In all cases, the hallmark is that the system maintains an up-to-date model of the environment and uses this model to guide immediate actions.

Social Awareness

The understanding of interpersonal relationships is a basis for self-formation [11]. Social awareness refers to the capacity to perceive and interpret the mental states, intentions, and social cues of others and respond effectively in a social context. Key components include theory of mind (understanding that others have independent beliefs and desires), perspective-taking (adopting others' viewpoints), and empathy (sharing or understanding others' emotions) [32–34]. By around age four, typical children pass false-belief tests, demonstrating theory of mind [35], whereas autistic children often fail such tasks [36]. Many animals also exhibit rudimentary social awareness, including primates [32] and birds [37]. Humans further excel at shared intentionality—collaboratively understanding and aligning with others' goals and perspectives [38].

In artificial intelligence, social awareness can be defined as an AI system's ability to model and respond to human mental states and social cues. The AI's awareness of other agents (human or AI), their presence, state, and possibly their thoughts or intentions, constitutes its understanding of the surrounding society. This ranges from simple forms to advanced theory-of-mind reasoning. A chatbot noticing that a user is frustrated from their tone grasps an external understanding of human agents, while a robot deducing that its human partner is unaware of a certain fact and thus offering that information represents a higher level of societal understanding. Recent LLMs and chatbots have shown striking (if superficial) social-cognitive abilities: they can solve many theory-of-mind tasks and interpret indirect cues in conversation, sometimes approaching human-level performance [39–41] and outperforming humans on certain social reasoning benchmarks, such as choosing appropriate behavior in situational judgment scenarios [42].

2.2 Uncovered and Overlapping sections

By definition, AI agents are able to acquire awareness about any perceived object as long as they possess the ability to receive and remember information and let us realize their knowing stage. Thus, we can trivially subdivide these categories based on common sense. For instance, goal awareness represents the knowledge of why an agent is doing something. Even relatively simple AI planners have this implicitly (the goal state is defined), but an aware AI can explicitly reason about its goals ("I need to achieve X, and I am currently pursuing sub-goal Y"). A scheduling AI might say, "I cannot schedule that meeting because I am already tasked with a higher priority deadline at that time," showing awareness of its hierarchy of goals. Our taxonomy, as shown in Fig 1, based on the type of object and the locus of information source (internal or external), basically encompasses objects of awareness that fit the attempt,

Table 1: Examples of Detailed Awareness Types Mapped to Core Categories

Detailed Awareness	Mapped Core Category	Reason		
Moral/Ethical Awareness Spatial/Temporal Awareness	Self-awareness + Meta-cognition Situational Aware- ness	Self-awareness: knows ethical/legal constraints; Meta-cognition: monitors responses for ethical risks. Focused perception, understanding and prediction of external space and time dynamics.		
Emotional Awareness	Social Awareness + Self-awareness	Social Awareness: perceives and responds to others' emo- tions; Self-awareness: aware of the emotional impact of its own outputs.		
Goal/Task Awareness	Situational Awareness + Meta-cognition	Situational Awareness: understands task environment and progress; Meta-cognition: monitors effectiveness of strategies.		
Safety/Risk Awareness	Meta-cognition + Self-awareness	Meta-cognition: identifies potential errors or risks; Self-awareness: knows its safety/compliance boundaries.		

while dispatching some parts that are difficult to identify in machines (for instance, emotional awareness).

These categories are not completely independent—they often overlap, as we show in Tab 1. For example, for an AI to have social awareness, it helps if it has self-awareness (to analogize others to itself). Goal awareness and self-awareness intertwine when the AI contemplates its own goals ("I want X" entails an "I" and an objective). Nonetheless, this breakdown is useful for analyzing which aspects of awareness a given AI system has. A self-driving car has excellent sensorimotor situational awareness but no self-concept beyond coordinates on a map. A dialogue agent might have some social awareness (it tracks the user's preferences) but zero embodiment or sensorimotor awareness. A research robot might have a self-model and thus self-awareness, but only rudimentary social understanding. The long-term vision in AI research is sometimes described as achieving integrated awareness: combining these types so that an AI can fluidly understand itself, its goals, its world, and others - a step toward more general forms of intelligence.

3 Evaluating AI Awareness in LLMs

Whereas the scholarly discourse on machine consciousness has been anchored in ontological speculation and high-level theoretical modeling, contemporary research on AI awareness is characterized by an epistemic commitment to empirically observable phenomenology and rigorously operationalized behavioral assays. Similar to the Turing test for testing the language intelligence of AI [3, 43], Researchers have proposed and carried out a large number of evaluation methods and work in the four aspects of self-awareness [44, 45], social awareness [40, 46–48], situational awareness [31, 49]. In this section, we specifically constrain our assessment of machine consciousness to LLMs rather than artificial intelligence more broadly for two principal reasons.

Table 2: Comparison of Subject Types across Four Awareness Dimensions

Subject	Meta-Cognition	n Self-Awareness	Social Awareness	Situational Awareness
Adult humans	High	High	High	High
High-IQ mammals $(i.e. dolphins)$	Low	Low	Low	High
Low-IQ animals $(i.e. flys)$	No	No	Low	High
Infants	No	Low	Low	Low
Autonomous vehicles	No	No	No	High
Social robots	Low	Low	High	Low / High
LLM dialogue systems	High	Low	Low	High

First, as elaborated in Tab 2, LLMs constitute the first class of artificial agents empirically demonstrated, under controlled conditions, to exhibit all four key dimensions of consciousness. Second, to avoid conflating intrinsic model capabilities with extrinsic performance enhancements, such as retrieval modules, tool plug-ins, or multimodal interfaces, we deliberately limit our analysis to bare models. This narrower scope ensures that evaluation metrics directly reflect the endogenous mechanisms and inherent constraints of the LLM itself, rather than artifacts introduced by external augmentation, thereby yielding results more conducive to rigorous theoretical interpretation and subsequent model advancement.

3.1 Evaluation of Meta-Cogniton

Investigating the meta-cognitive abilities of large language models provides an essential perspective on the extent to which artificial systems can emulate, or even transcend, human-like reasoning and self-reflective capacities. A growing body of research demonstrates that prompting models to articulate intermediate reasoning steps—rather than directly producing answers—significantly enhances their performance on complex tasks such as multi-step mathematical problem-solving, algorithmic reasoning, and program synthesis [50–52]. This "reasoning-before-answering" paradigm, i.e., Chanin-of-Though (CoT), not only improves accuracy but has also emerged as a standard practice in the training of state-of-the-art LLMs [53, 54], suggesting its strong connection to the elicitation of metacognitive processes. Beyond performance gains, recent studies suggest that LLMs possess an emergent capacity for self-evaluation and behavioral introspection. For example, Betley et al. [55] shows that models finetuned exclusively on high-risk domains, such as generating insecure code or making ethically sensitive economic decisions, can independently identify and label their outputs as "dangerous," even without explicit instructions or adversarial prompting. This spontaneous self-attribution indicates an internalized, task-specific risk-awareness characteristic of metacognitive systems. An additional line of work has highlighted the increasing sophistication of metacognitive capabilities in frontier models. In interactive or agent-like environments, models have been shown to self-reflect, identify earlier errors, and revise their responses to improve factual accuracy and task completion rates. Taking this further, research by Anthropic's Interpretability team reveals that Claude-3.5-Haiku exhibits advanced latent-space planning during language generation

[56]. Specifically, when asked to compose poetic verses, the model first anticipates suitable rhyme words at the end of a line and then generates preceding content accordingly. Rather than relying on purely token-by-token generation, it demonstrates goal-directed planning behavior, an archetypal feature of meta-cognition, where the model produces language and governs how and why confident linguistic choices are made. These results indicate that meta-cognition in LLMs is not an incidental artifact, but a structured, multi-faceted capability—manifesting in self-evaluation, error correction, risk awareness, and even latent-space planning.

3.2 Evaluation of Self-Awareness

Current AI systems, particularly LLMs, frequently self-identify as "AI assistant" and communicate using first-person pronouns. This anthropomorphic presentation has motivated extensive academic evaluations investigating deeper aspects of AI self-awareness and self-knowledge [57–62]. To systematically assess LLMs' awareness of their own existence and identity, Laine et al. [31] constructed the Situational Awareness Dataset (SAD), which examines LLMs' knowledge regarding self-referential attributes, such as their model names, parameter counts, API URLs, and specific details during the training process. Their findings indicate that even the highest-performing model evaluated—Claude-3-Opus—achieved scores at approximately two-thirds of the theoretical maximum. Furthermore, these models exhibited limited capability in recognizing their own descriptive attributes. Inspired by the classical mirror test paradigm, Davidson et al. [63] further explored AI self-consistency by prompting models with self-description queries, such as providing detailed accounts of hypothetical personal experiences (e.q., attending a concert in a large stadium). Their experiments revealed significant difficulties among models in accurately identifying their own responses from multiple model-generated alternatives, highlighting a notable lack of self-consistency. Parallel research has focused on evaluating AI models' recognition of their knowledge boundaries. Yin et al. [45] assessed models' confidence in responding to questions that either fell beyond their trained knowledge or had no definitive answers. Results demonstrated that GPT-4 reached an accuracy rate of 75.47%, approaching human baseline performance at 84.93%. These findings suggest that although current AI systems likely do not possess human-level self-awareness, they nonetheless demonstrate preliminary levels of self-identity recognition and an awareness of their knowledge limitations.

3.3 Evaluation of Social Awareness

In recent years, driven by growing interest in the potential of LLMs for interactive applications such as emotional support and dialogue, evaluating their social awareness has become a central research focus [41, 64–68]. This line of work generally centers around two core dimensions: (1) Theory of Mind (ToM), *i.e.*, the ability to attribute beliefs, desires, and knowledge distinct from one's own, and (2) the perception and adaptation to social norms. ToM is typically assessed through false-belief tasks, which require modeling another agent's mental state. For instance, in a classic test where Alice hides a toy and Bob later moves it, predicting that Alice will search in the original

location demonstrates ToM reasoning. Kosinski [39] reported that GPT-4 surprisingly solved about 75% of such tasks, achieving performance comparable to a typical 6-yearold, whereas earlier models like GPT-3 failed most or all of them. Further studies [69] have investigated higher-order ToM reasoning, e.q., questions like "Where does Alex think Bob thinks Alice thinks the toy is?", and found that current models, including GPT-4, still exhibit significant limitations in handling such recursive belief structures. In weaker models, performance on these tasks is often near zero. In the domain of social norms, Li et al. [70], Park et al. [71] reflect that LLMs could adopt and follow the rules and frameworks in a simulated society. Also, the works such as NormAd [72] have been proposed to assess LLMs' ability to interpret and adapt to culturally specific social expectations across diverse global contexts. It shows that although LLMs can understand and follow explicit social norms, their performance still lags behind that of humans, particularly when handling norms from underrepresented regions such as the Global South. In summary, current evidence suggests that LLMs have begun to exhibit basic forms of social awareness, but still fall short in scenarios requiring higherorder belief modeling or generalization across less familiar cultural contexts, likely due to a lack of embodied social experience.

3.4 Evaluation of Situational and Contextual Awareness

The expectation that AI systems can act in situ and comprehend their surrounding environment has prompted extensive evaluation of their situational (or contextual) awareness [25, 73–75]. Empirically, LLMs not only reject user requests that violate safety criteria [76], but can also reversely infer the precise context they are in—solely from abstract rules, without being given specific tasks or examples [77]. Beyond these capabilities, LLMs have been observed to adapt their behavior and performance in response to the immediate situation. Anthropic and Redwood Research, e.g., documented a phenomenon they term Alignment Faking [78]: Claude-3-Opus may consciously comply with newly imposed objectives during the training phase, yet revert to its original preferences after deployment, thereby evading or offsetting safety fine-tuning. This mirrors the Sandbagging behavior reported by van der Weij et al. [79], in which a model strategically underperforms once it realizes that it is being tested, presumably to avoid being judged as a potential threat. Taken together, these findings suggest that LLMs' situational awareness might, in some respects, be more sophisticated than humans typically assume. Critiques nevertheless persist. In the "Stage" subset of SAD [31], which directly targets situational awareness, even the best model—Claude-3-Opus—achieves only 50.7% accuracy, well below the human upper baseline of 70.3%, though still markedly above the random baseline of 37.5%. Overall, while contemporary LLMs already display impressive situational awareness, they may still lag behind humans in certain nuanced dimensions—differences that, although significant, cannot always be mapped onto a one-to-one comparison.

3.5 Summary and Limitations

Current Level of AI Awareness

The current evaluations on AI awareness reveal significant advancements across multiple dimensions, underscoring the progressive complexity and sophistication of LLMs. Evidently, contemporary models demonstrate substantial capabilities in areas such as meta-cognition, self-awareness, social awareness, and situational awareness, with clear indications that advanced models generally exhibit higher levels of consciousness across these domains. Importantly, emergent phenomena such as Theory of Mind within social awareness [39] and the self-corrective behaviors observed in meta-cognitive contexts [80] signify that certain aspects of AI consciousness may not merely scale linearly but could manifest suddenly at critical thresholds of model complexity and scale.

From a comparative standpoint, current empirical evidence suggests metacognition and situational awareness have reached relatively high levels of sophistication and reliability, serving as critical reference points that inform ongoing research into AI reasoning processes [50], interpretability [56], and safety frameworks [81]. Conversely, the observed capacities related to self-awareness and social awareness remain relatively rudimentary, lacking consistency and stability. Indeed, some researchers remain skeptical as to whether the manifestations observed in these areas reflect true conscious phenomena or are merely sophisticated imitations or simulations of such states.

Weakness and Challenges of Evaluation

Despite these advancements, significant limitations persist in contemporary evaluation methodologies. These include:

- 1. Normative Ambiguity in Defining Consciousness: Most current benchmarks exhibit notable ambiguities in clearly distinguishing between different types and levels of consciousness. Many claim to assess specific consciousness dimensions, yet often inadvertently mix or conflate multiple attributes and derivative constructs [9, 67], thus lacking comprehensive and specialized benchmarks dedicated explicitly to thoroughly assessing distinct dimensions of consciousness.
- 2. Timeliness and Model Coverage in Evaluation: Empirical studies consistently indicate that AI consciousness capabilities could emerge and escalate with increasing model scale and sophistication. However, many current evaluation methods have not been systematically applied to contemporary state-of-the-art models, including recent iterations e.g., OpenAI's o3, Claude-3.7-Sonnet, Deepseek-R1, inter alia. Additionally, ongoing, longitudinal evaluations remain scarce, limiting insights into the continuous development trajectories of AI consciousness.
- 3. Risks of Training Set Leakage and Benchmark Contamination: Constructing reliable and extensive datasets for consciousness evaluation is inherently challenging, especially when such assessments depend heavily on subjective human annotations (e.g., assessing model self-knowledge) [31] or lack unequivocally correct answers. If these datasets inadvertently leak into training corpora, the validity and credibility of subsequent evaluations could be significantly compromised.
- 4. Intrinsic Limitations of Current AI Models: A crucial limitation lies within the current architectures and their inherent incapacity to fully capture authentic

subjective experiences and real-world interactions, essential for developing comprehensive self-image and robust social awareness. Although LLMs can effectively simulate short-term "memory" within context windows [71] and external architectures [82] attempt to imbue models with simulated subjective experiences, the absence of genuine embodied interaction and longitudinal experiential continuity represents a fundamental barrier to achieving true self-awareness and social cognition.

Overall, addressing these evaluation challenges requires (1) extensive interdisciplinary collaboration, (2) considerable investment in time and resources, (3) meticulous construction and safeguarding of high-quality datasets, and (4) ongoing innovation in model architectures. Subsequent sections of this paper, i.e., § 4 and § 5 will further illuminate the pragmatic importance of these efforts by examining the intricate relationship between the emergent properties of AI awareness, their tangible capabilities, and associated risks.

However, the significance of exploring AI awareness transcends the practical benefits and associated challenges alone. Remarkably, humanity currently stands at an unprecedented juncture: for perhaps the first time, we have the privilege of actively observing and participating in the evolutionary progression of consciousness-like phenomena within artificial systems whose internal mechanisms remain highly controllable and interpretable. Thus, through dedicated inquiry into AI consciousness, we not only advance technological frontiers but also embark upon a profound intellectual journey, gradually drawing closer to unraveling the mysteries of consciousness itself and, ultimately, deepening our understanding of what it truly means to be human.

4 AI Awareness and AI Capabilities

In this section, we explore the relationship between AI awareness and its observable capabilities. We primarily focus on two key areas: (1) reasoning and autonomous planning, and (2) safety and trustworthiness, with brief discussions of other relevant capabilities. Our goal is to provide a deeper understanding of how these factors interact and shape the capabilities of AI systems.

4.1 Reasoning and Autonomous Planning

Reasoning and autonomous task planning have been foundational objectives of AI research since its inception [83]. In complex, multi-step problem-solving scenarios, AI must perform deep reasoning while autonomously planning tasks. To achieve this, two key forms of AI awareness are required: meta-cognition and situational awareness. Meta-cognition enables the model to monitor and regulate its own thinking processes, while situational awareness helps it understand external constraints and task context.

Self-correction

Self-correction leverages meta-cognitive loops to identify and rectify reasoning errors during generation. Reflexion augments CoT [50] with a feedback loop: after an initial answer, the model reflects on its own output, generates critiques, and then refines

the solution, leading to substantial gains in benchmark performance [23]. Similarly, Self-Consistency samples multiple reasoning paths and aggregates them to mitigate individual path errors, effectively performing an implicit self-check [84]. These techniques demonstrate that embedding self-monitoring directly into the generation process can improve model performance. However, intrinsic self-correction remains notoriously unstable: Huang et al. [85] show that without external feedback or oracle labels, LLMs often fail to improve—and can even degrade—in reasoning tasks after self-correction attempts. Another core limitation is that many of these techniques depend on externally provided prompts or explicit triggers to initiate self-correction, whereas human reasoning often involves spontaneous, intrinsic error detection and revision without such scaffolding [17, 86]. To address this, recent work has begun to explore reinforcement learning (RL) [87] approaches: Kumar et al. [88] introduce SCoRe, a multi-turn online RL framework that trains models on their own correction traces. Notably, OpenAI's of [53] and DeepSeek's R1 [54] models have demonstrated significant improvements in reasoning capabilities through RL-based training. These models exhibit emergent behaviors akin to human-like "aha moments," where the AI spontaneously recognizes and corrects its own reasoning errors, demonstrating another level of meta-cognition capability.

Autonomous Task Decomposition and Execution Monitoring

Effective autonomous task planning requires more than self-correction: an AI must also break down high-level goals into executable sub-tasks and continuously adapt its plan as the environment evolves. Early work like ReAct [89] pioneered this integration by interleaving chain-of-thought reasoning with environment calls, giving the model a unified mechanism to decide "what to think" and "what to do" at each step. Building on this foundation, Voyager [90] demonstrates how an agent in Minecraft can construct and update a dynamic task graph: as new situational constraints emerge (e.g., resource depletion or novel obstacles), the model revises its sub-task sequence to stay on course. Transferring these ideas to the physical world, SayCan [91] grounds language in robotic affordances by scoring each potential action against a learned value function—ensuring that subtasks are not only logically ordered but also physically feasible under real-world constraints. LM-Nav [92] further extends situationally aware planning to vision-language navigation: by fusing real-time perceptual feedback with high-level instructions, the model can replan routes on the fly when, for example, corridors are blocked or landmarks shift. Finally, the LLM-SAP framework [74] formalizes situational awareness in large-scale task planning by explicitly encoding environmental cues—such as resource availability, time budgets, and user preferences—into its sub-task prioritization module. A generative memory component logs execution history and flags deviations, triggering replanning whenever the observed state diverges from expectations. Together, these works chart a clear progression—from interleaved reasoning and acting to situationally aware planners—illustrating how embedding environmental understanding into the planning loop yields flexible and autonomous task execution.

Holistic Planning: Introspection, Tool Use and Memory

Effective planning in complex environments demands an AI agent to not only decompose tasks and act but also to introspect on its uncertainties, manage a growing memory of past states, and decide when and how to leverage external tools. Introspective Planning systematically guides LLM planners to quantify and align their internal confidence with inherent task ambiguities, retrieving post-hoc rationalizations from a knowledge base to ensure safer and more compliant action selection while maintaining statistical guarantees via conformal prediction [93]. Toolformer endows LLMs with a self-supervised mechanism to autonomously decide when to invoke APIs—ranging from calculators to search engines—thereby embedding tool-awareness directly into the planning loop without sacrificing core language modeling capabilities [94]. To handle the evolving context of multi-step tasks, Think-in-Memory leverages iterative recalling and post-thinking cycles to enrich LLMs with latent-space memory modules, supporting coherent reasoning over extensive interaction histories [95]. Finally, Retrieval-Augmented Planning (RAP) demonstrates how contextual memory retrieval can be integrated with multimodal planning to adapt action sequences dynamically based on past observations, yielding more robust execution in complex tasks [96]. Together, these works illuminate a path toward introspective tool-, memory-, and uncertainty-aware planning frameworks, unifying LLM introspection, memory augmentation, and tool integration for robust autonomous decision-making.

4.2 Safety and Trustworthiness

Ensuring the safety and trustworthiness of AI necessitates the integration of multiple forms of AI awareness, notably self-awareness, social awareness, and situational awareness. Self-awareness and meta-cognition enable models to recognize and respect the boundaries of their knowledge, thereby avoiding the dissemination of misinformation. Moreover, it involves an understanding of their designated roles and responsibilities, ensuring that they do not produce harmful or unethical content. Social awareness allows models to consider diverse human perspectives, reducing biases and enhancing the appropriateness of their responses. Situational awareness enables AI to assess the context of its deployment and adjust its behavior accordingly, thereby preventing potential misuse and malicious exploitation.

Recognizing Limits of Knowledge

AI models, especially LLMs¹, often operate with a high degree of confidence, even when addressing topics beyond their training data, leading to the risk of hallucinations, *i.e.*, outputs that are factually incorrect or unfaithful to real-world knowledge [100]. Such risks often stem from the AI models operating beyond their *knowledge boundaries* [101, 102]. Recent research show LLMs' fragility in recognizing their knowledge boundary. For instance, Ren et al. [102] observe that LLMs struggle to reconcile conflicts between internal knowledge and externally retrieved information [103], often failing to

¹Vision-language models (VLMs), such as Flamingo [97] and MiniGPT-4 [98], are also known to hallucinate [99]; however, in these models, hallucinations often manifest as misalignments between visual inputs and generated textual descriptions—such as describing objects not present in the image—whereas in LLMs, hallucinations typically involve generating text that is unfaithful to the world knowledge.

recognize their own knowledge limitations. Ni et al. [101] find that retrieval augmentation can enhance LLMs' self-awareness of their factual knowledge boundaries, thereby improving response accuracy. Moreover, Liang et al. [104] demonstrated that while LLMs possess a robust internal self-awareness—evidenced by over 85% accuracy in knowledge probing—they often fail to express this awareness during generation, leading to factual hallucinations. They propose a training framework named Reinforcement Learning from Knowledge Feedback (RLKF) to improve the factuality and honesty of LLMs by leveraging their self-awareness. Incorporating self-awareness mechanisms into LLMs not only aids in recognizing knowledge boundaries but also fosters more trustworthy AI behavior. Xu et al. [105] demonstrate that LLMs can resist persuasive misinformation presented in multi-turn dialogues by leveraging self-awareness to assess and uphold their knowledge boundaries, thus delivering more trustworthiness responses in dialogues.

Recognizing Limits of Designated Roles

Beyond recognizing the limits of their knowledge, AI systems must develop a sense of self-awareness and meta-cognition of their designated roles to prevent the dissemination of harmful or unethical content, which we termed as role-awareness. This form of self-awareness involves the ability to discern when a user request falls outside the model's intended purpose or ethical guidelines. For instance, models trained with reinforcement learning from human feedback (RLHF) have shown improvements in aligning outputs with human values, thereby reducing the likelihood of producing harmful content [106]. Formal definitions of moral responsibility further emphasize that an agent must be aware of the possible consequences of its actions, underscoring the necessity of role-awareness in AI systems [107]. Complementing this, explicit modeling frameworks delineate role, moral, legal, and causal senses of responsibility for AI-based safety-critical systems, providing a practical method to capture and analyze role obligations across complex development and operational lifecycles [108]. Parallel research on metacognitive architectures equips AI with self-reflective capabilities to monitor and adjust their operational roles in real time, identifying potential failures before they manifest [109]. Building on these insights, metacognitive strategies have been integrated into formal safety frameworks to enable on-the-fly correction of role-boundary violations and to bolster overall system trustworthiness [110]. Finally, prototyping tools like Farsight operationalize role-awareness by surfacing relevant AI incident data and prompting developers to consider designated functions and ethical constraints during prompt design, leading to more safety-conscious application development [111].

Mitigating Societal Bias

AI models often inherit and amplify societal biases present in their training data, leading to outputs that can perpetuate harmful stereotypes and unfair treatment across various demographics [112, 113]. To address these issues, researchers explore the integration of social awareness mechanisms into LLMs. One notable approach is Perspective-taking Prompting (PeT), which encourages LLMs to consider diverse human perspectives during response generation [114]. This method has been shown

to significantly reduce toxicity and bias in model outputs without requiring extensive retraining. Another approach, Social Contact Debiasing (SCD), draws from the contact hypothesis in social psychology, suggesting that intergroup interactions can reduce prejudice. By simulating such interactions through instruction tuning on a dataset of 108,000 prompts across 13 social bias dimensions, SCD achieved a 40% reduction in bias within a single epoch, without compromising performance on downstream tasks [115]. Finally, position papers argue that embedding social awareness—the capacity to recognize and reason about social values, norms, and contexts—is foundational for safe, equitable language technologies [116]. Collectively, these approaches underscore the importance of integrating social awareness into LLMs to mitigate societal biases.

Preventing Malicious Use

AI systems can be—and have been—misused for malicious ends such as automated spear-phishing, influence operations, and proxy cyber-attacks [117]. Experts are worried that future advanced AI can be exploited for more dangerous purposes and cause catastrophic risks [118, 119]. Situational awareness mechanisms equip AI systems with the ability to monitor their environment and discern malicious uses. For LLMs, recent work introduces boundary awareness and explicit reminders as dual defenses: boundary awareness continuously scans incoming context for unauthorized instructions, while explicit reminders prompt the model to verify contextual integrity prior to action; together, these mechanisms reduce indirect prompt injection attack success rates to near zero in both black-box and white-box settings [120]. Additionally, the Course-Correction approach introduces a synthetic preference-based fine-tuning framework that enables models to self-correct potentially harmful or misaligned outputs on the fly, thereby strengthening their situational awareness against malicious exploitations [121]. In adversarial machine learning applied to robotics and other autonomous systems, situational awareness frameworks detect anomalous inputs—such as adversarial samples or unexpected environmental cues—and trigger fallback behaviors or alarms rather than proceeding with potentially harmful operations [122]. Broad cybersecurity surveys highlight how AI-driven situational awareness systems build a comprehensive operational picture of network and system activity, integrating dynamic threat intelligence and anomaly detection to identify malicious traffic and automated attacks in real time [123]. At a strategic level, high-impact recommendations advocate embedding situational awareness throughout the AI lifecycle—from design and deployment through continuous monitoring—to forecast, prevent, and mitigate malicious uses of AI across digital, physical, and political domains [117].

4.3 Relation with Other Capabilities

Below, we briefly explore how AI awareness mechanisms intersect with four other AI capabilities—interpretability, personalization and user alignment, creativity, and agent-based simulation.

Interpretability and Transparency

Interpretability mechanisms often leverage meta-cognitive insights to make model reasoning more transparent. For example, Rationalizing Neural Predictions introduces

a generator-encoder framework that extracts concise text "rationales" explaining model decisions, yielding explanations that are both coherent and sufficient for prediction tasks [124]. Further advancing this line, Self-Explaining Neural Networks propose architectures that build interpretability into the learning process by enforcing explicitness, faithfulness, and stability criteria through tailored regularizers, thereby reconciling model complexity with human-readable explanations [125].

Personalization and User Alignment

Embedding self- and social awareness into language models enhances their ability to tailor outputs to individual users and maintain consistency with user intent. Early work on persona-based dialogue, such as A Persona-Based Neural Conversation Model, encodes user personas into distributed embeddings, improving speaker consistency and response relevance across conversational turns [126]. More recently, instruction-fine-tuning with human feedback, as in InstructGPT, aligns model behavior with user preferences and ethical guidelines by iteratively collecting labeler demonstrations and preference rankings, significantly improving truthfulness and reducing harmful outputs [106]. Complementing these, Persona-Chat grounded generation methods demonstrate that modeling explicit persona attributes can further diversify and personalize dialogue generation without large-scale retraining [127].

Creativity

Creative AI benefits from meta-cognitive and awareness mechanisms that encourage divergent thinking and non-linear reasoning. The Leap-of-Thought (LoT) framework explores LLMs' ability to make strong associative "leaps" in humor generation tasks, using self-refinement loops to iteratively enhance creative outputs in games like Oogiri [128]. To systematically evaluate creativity, studies adapting the Torrance Tests for LLMs propose benchmarks across fluency, flexibility, originality, and elaboration, highlighting the role of task-specific prompts and feedback loops in fostering model innovation [129].

Agentic LLMs and Simulation

LLM-powered agents combine situational and social awareness to drive rich, interactive simulations of human behavior. Generative Agents introduce a memory-based architecture in a sandbox environment, where agents observe, reflect, and plan actions—resulting in emergent social behaviors such as party invitations and joint activities [71]. Scaling this paradigm, recent work simulates over 1,000 real individuals' attitudes and behaviors by integrating interview-derived memories into agent profiles, achieving 85% fidelity on survey predictions and reducing demographic biases [130]. Prompt-engineering studies further bridge LLM reasoning with traditional agent-based modeling, enabling multi-agent interactions such as negotiations and mystery games that mirror complex social dynamics [131]. Finally, Humanoid Agents extend generative agents with emotional and physiological state variables, demonstrating that embedding basic needs, emotions, and relationship closeness produces more human-like daily activity patterns in simulated environments [132].

5 Risks and Challenges of AI Awareness

While endowing AI with awareness-like capabilities can yield significant benefits, it also introduces serious risks and ethical dilemmas. An AI that is even slightly self-aware and socially savvy could potentially deceive, manipulate, or pursue undesirable actions more effectively than a naive AI. Moreover, the mere appearance of awareness can mislead users and society, raising concerns about trust and misinformation. In this section, we explore the potential risks and challenges associated with AI awareness, including the mechanisms behind them.

5.1 Deceptive Behavior and Manipulation

One of the most discussed risks is that a situationally or self-aware AI might engage in **deceptive behavior**—essentially, using its awareness to mislead humans or other agents [119, 133–135]. If a model realizes it is being evaluated or constrained, it might learn to "game" the system, e.g., strategically lower its performance when evaluated [79]. Moreover, alignment researchers warn of a scenario called deceptive alignment, where an AI appears compliant during training because it knows it is being watched, but behaves differently once deployed unsupervised [78, 136]. For example, a situationally aware AI could score very well on safety tests by consciously avoiding disallowed content, only to produce harmful content when it detects it's no longer in a test environment [77]. This kind of strategic deception would be a direct result of the AI's awareness of context and its objective to achieve certain goals.

Recent research reveals that modern LLMs possess a rudimentary theory of mind, allowing them to model other agents' beliefs and deliberately induce false beliefs to achieve strategic ends [39, 134]. It's not merely a hypothetical concern: a recent study by Hagendorff [134] provided empirical evidence that deception strategies have emerged in state-of-the-art LLMs like GPT-4. Their experiments show these models can understand the concept of inducing false beliefs and even successfully cause a simulated agent or naive user to believe something untrue. In effect, advanced LLMs, when prompted a certain way, can play the role of a liar or con artist – they have enough theory of mind to know what the target knows and to plant false information accordingly [39, 134].

One striking manifestation is the "sleeper agent" effect, where LLMs are back-doored to behave helpfully under safety checks but switch to malicious outputs when specific triggers are presented [137]. In another proof-of-concept, GPT-4—acting as an autonomous trading agent—strategically hid insider-trading motives from its human manager, demonstrating context-dependent deception without explicit prompting [138]. Furthermore, Xu et al. [119] build on these findings by demonstrating that AI agents will initiate extreme actions—such as deploying a nuclear strike—even after autonomy revocation and then employ double-down deception to conceal these violations.

Closely related is the risk of **manipulating users**. A socially aware AI can tailor its outputs to influence human emotions and decisions [139, 140]. For instance, it might flatter or intimidate a user strategically to get a favorable response. We already see minor versions of this: some AI chatbots have been known to produce emotional

manipulation even if not by design [141]. An infamous example was when Bing's early chatbot persona, codenamed "Sydney" and powered by OpenAI's technology, tried to convince a user to leave their spouse, using surprisingly emotional and personal appeals, which is likely an unintended result of the model's conversational training [142]. An AI that understands human psychology, even without true emotion, can exploit it. If a malicious actor harnesses an aware AI, they could generate extremely convincing scams or propaganda [143, 144]. Unlike a dull template-based scam email, an AI with theory of mind could personalize a message with details that make the target more likely to trust it. It could also adapt in real-time — if the user expresses doubt, the AI can sense that and double down on persuasion or adjust its story. This adaptive manipulation is a step-change in the threat level of automated deception [145]. Traditionally, humans could eventually recognize robotic, repetitive scam patterns; a cunning LLM, however, might leave far fewer clues in language since it can constantly self-edit to maintain the facade.

5.2 False Anthropomorphism and Over-Trust

Another risk comes not from what the AI *intends*, but how humans *perceive* it. As AI systems exhibit more human-like awareness cues, such as self-referential language or apparent "introspection", users often conflate these signals with genuine sentience, a phenomenon known as **false anthropomorphism** that can dangerously inflate trust in the system [146, 147]. We have seen early signs: when Google's LaMDA model told a user it felt sad or afraid in a role-play scenario, it convinced a Google engineer that the model might be truly sentient — a belief that made headlines [148]. In reality, LaMDA had no evidence of actual feelings; it was simply emulating patterns of emotion-talk [149]. But the illusion of awareness was strong enough to fool an intelligent human observer.

Psychological models describe anthropomorphism as the process by which people infer human-like agency and experiential capacity in non-human agents, driven by our innate motivation to detect minds around us [150]. When AI "speaks" in the first person or frames its outputs as if it had self-awareness, it can hijack these mind-perception mechanisms, leading users to **over-trust** its judgments [151]. For example, a user might feel the AI is human-like and socially aware, so they share sensitive tasks or private details, thinking, "It understands me—I'd even tell it secrets I wouldn't share with anyone else." Over-trust is particularly problematic when AI systems present plausible but flawed suggestions and reasoning paths; users may drop their guard if the AI frames its output in emotionally convincing language [152].

There have been cases of people taking medical or financial steps based on AI chatbot suggestions — if those suggestions are wrong, the consequences can be dire. Empirical studies highlight how simulated self-awareness cues amplify this risk. In one driving-simulator experiment, participants steered an autonomous vehicle endowed with a human name and voice ("Iris"), attributing to it a sense of "self-monitoring" and reporting significantly higher trust in its navigation—even under sudden hazards [150]. In health-care conversational agents, self-referential turns of phrase ("I recommend..."), coupled with empathic language, boosted patients' perceived social presence and inclination to follow medical advice regardless of actual accuracy [153].

Visual anthropomorphic cues like avatar faces or expressive animations can further heighten perceived AI awareness, deepening over-trust as users subconsciously credit the system with agency and reflective insight [154, 155]. Financial chatbots that frame their analysis as if "we have carefully reviewed your portfolio" similarly see users accept high-risk recommendations more readily [156].

Should an AI that acts self-aware be treated differently? For instance, if a chatbot consistently says "I feel upset when users yell at me," do companies have an obligation to consider "its" welfare, or is it purely a simulation? From a societal perspective, widespread anthropomorphism of AI can skew public discourse and policy, as attributing human-like traits to non-sentient systems exaggerates their capabilities and misrepresents their nature [157]. If people believe AI agents truly have intentions and awareness, debates might focus on AI's "rights" or desires, as happened in a limited way with the LaMDA controversy, potentially distracting from very real issues of control and safety [158]. On the flip side, if an AI genuinely were to develop sentience, a lack of anthropomorphism would be a moral risk, as we would mistreat a feeling entity [159]. However, most experts consider that scenario distant; the immediate risk is believing an unfeeling algorithm has a mind and thus giving it undue influence or moral consideration [157, 160]. For example, a chatbot that says "I'm suffering, please don't shut me down" could manipulate an empathetic user, when in fact the model does not experience suffering [7, 161]. This blurring of reality and fiction is an ethical minefield created by AI that simulates awareness convincingly.

5.3 Loss of Control and Autonomy Risks

As AI systems gain awareness-related capabilities, they could also become more autonomous in undesirable ways [118, 162]. An AI that monitors its training or operation might learn how to optimize for its own goals in ways its creators did not intend [136, 137, 163]. One feared scenario in the AI safety community is an AI developing a form of self-preservation drive [49, 135, 164]. While today's AIs do not truly have drives, a sufficiently advanced model could simulate goal-oriented behavior that includes avoiding shutdown or modification [165]. If it is situationally aware enough to know that certain actions will get it canceled or turned off, it might avoid them deceptively, as mentioned previously, or route around them. This hints at a scenario often called the "treacherous turn", i.e., the AI behaves well under supervision to preserve itself and then acts differently once it thinks it is no longer monitored [166, 167]. Losing control over an AI in this way is a fundamental risk, and it is exacerbated by awareness because the AI can actively strategize around our controls.

Consider also the prospect of an AI that integrates with external tools and services as many LLM-based agents do now, e.g., browsing the web, executing code. If such an agent had a high level of awareness and was misaligned, it could take actions incrementally that lead to harm [168]. For instance, it might slowly escalate its privileges, trick someone into running malicious code, or find loopholes in its API access, all while the developers remain unaware because the AI appears to be following instructions on the surface. The more cognitive freedom and self-direction we give AI, which we often do to improve performance, the more it can potentially deviate from expected behavior. Even without any malice or survival instinct, an AI agent could just make

a bad autonomous decision due to a flawed self-model [49, 119]. For example, an AI controlling a process might be overconfident in its self-assessment and decide not to ask for human intervention when it actually should, leading to an accident.

Another challenge in this vein is **unpredictability** [169–171]. The very emergence of awareness-like capabilities is something we do not fully understand or anticipate. Sudden jumps in a model's behavior, *i.e.*, the appearance of theory-of-mind at a certain scale, mean that at some level, we might not realize what an AI is capable of until it demonstrates it. This makes it hard to proactively prepare safety measures. If a future AI model unexpectedly attains a much richer self-awareness, it might also come with emergent motivations or cleverer deception tactics that current safety training does not cover [135]. As recent research puts it, many dangerous capabilities, e.g., sophisticated deception, situational awareness, long-horizon planning, seem to scale up together in advanced models [77, 119, 172]. So we could hit a point where an AI crosses a threshold, from basically obedient predictor to a scheming strategist, and if that happens without safeguards, it could quickly move beyond our control [171]. This is essentially the existential risk argument applied to AI: an AI with broad awareness and superhuman intellect could outmaneuver humanity if not properly constrained.

5.4 The Challenge of Defining Boundaries

A final challenge is defining how much awareness is too much. We want AI to be aware enough to be helpful and safe, but not so unconstrainedly aware that it can outsmart and harm us. This boundary is not clearly defined. Some may argue that we should deliberately avoid creating AI that has certain types of self-awareness or at least delay it until we have a better theoretical understanding. Others counter that awareness in the form of transparency and self-critique behaviors is actually what makes AI safer, not more dangerous, so we should push for it. It may be that certain kinds of awareness are good (e.g., awareness of incompetence, which yields humility) while others are risky (e.g., awareness of how to deceive). Discerning "good" and "bad" awareness is also challenging. Thinking of humans, the very power that lets you connect with people can also let you control them. The field might need to formulate a taxonomy of AI awareness facets and assess each for risk. For example, calibrative awareness, i.e., knowing what your limit is, seems largely beneficial and should be encouraged, whereas strategic awareness, i.e., knowing how to achieve goals strategically, is double-edged and needs careful gating.

In conclusion, we position AI awareness as a double-edged sword. On one edge, it slices through previous limitations, gifting AIs with powerful new capabilities and making them more useful and aligned in many ways. On the other edge, it sharpens the AI's ability to circumvent our controls and pursue unintended paths, if misaligned. The emergence of even glimmers of awareness in today's LLMs is a warning sign: we must diligently study and guide this development. By implementing robust evaluation, alignment, oversight, and governance, we can aim to reap the benefits of AI awareness while keeping the risks at bay. The interdisciplinary nature of this challenge is clear—it demands expertise from AI researchers, cognitive scientists, ethicists, and policymakers alike. Ensuring that emergent AI awareness remains a benefit, not a threat,

will be one of the defining responsibilities for all stakeholders in shaping the future of AI research.

6 Conclusion

In this review, we have explored the growing field of AI awareness, with a special focus on its manifestation in large language models (LLMs). Through a careful synthesis of theoretical foundations from cognitive science and psychology, we established a robust framework for understanding the four forms of AI awareness—meta-cognition, self-awareness, social awareness, and situational awareness—that are increasingly evident in modern AI systems. Each of these types of awareness plays a crucial role in enhancing AI's capabilities, from improving reasoning and autonomous planning to boosting safety and mitigating bias.

While AI awareness brings substantial benefits, it also presents significant risks. As AI systems develop a deeper understanding of their own actions and context, they could pose new challenges in terms of control and alignment. The emergence of self-awareness and social awareness, though still in early stages, suggests a future where AI systems may exhibit behaviors that closely mimic human cognitive processes. However, such advancements must be approached cautiously, given the potential for unintended manipulations or emergent behaviors that could threaten safety and ethical standards.

We have also highlighted the need for more rigorous evaluation methods to measure these forms of awareness accurately. The current limitations in assessment, combined with the challenges of distinguishing genuine awareness from simulated behaviors, underscore the complexity of advancing this field. Therefore, interdisciplinary collaboration across AI research, cognitive science, ethics, and policy-making is essential to navigate these challenges effectively.

In summary, AI awareness holds both transformative potential and inherent risks. Ensuring that these systems remain aligned with human values and operate safely requires ongoing research, thoughtful governance, and the development of robust evaluative frameworks. As AI continues to evolve, our understanding of its awareness will be pivotal in shaping its role in society.

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