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The Changing Cognitive Role of Product Managers in the Age of AI: Why Human Judgment Alone Is No Longer Sufficient

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Abstract

Purpose: As the environments in which products operate become ever more data-rich, dynamic, and interconnected, PMs must balance customer telemetry, experimentation, and market intelligence with stakeholder requirements, making decisions that are critical and time-sensitive at the same time. Using bounded rationality and cognitive theory, this study investigates the evolving PM role from individual sense-making to managing human-AI systems for decision-making. This study posits that the adoption of AI technology is no longer merely an enabler of efficiency gains but a cognitive necessity for effective decision-making, considering the detrimental effects of information overload on decision-making performance and well-being (Arnold et al., 2023).

Materials and Methods: The research design is based on a descriptive and explanatory research model that integrates literature from decision theory, cognitive science, and knowledge management with survey data from practicing product managers in technology-driven organizations (n=174). The key areas of focus in the research include the cognitive load, decision fatigue, prioritization, speed of execution, and the use of AI-based decision support.

Findings: The results reveal that Product managers (PMs) who lack AI-based decision support systems are likely to experience cognitive overload, decision fatigue, unclear prioritization, and slower execution cycles. Conversely, using AI-based systems can lead to better information triage, improved pattern detection, and increased confidence in trade-off decisions. In line with previous research on human-AI collaboration, the results reveal that task-type and design-based effects of using AI-based systems can lead to coordination losses when poorly designed (Vaccaro et al., 2024).

Implications to Theory, Practice, and Policy: The study contributes to the development of the theory of bounded rationality by placing artificial intelligence as a cognitive augmentation layer in product decision systems, rather than replacing human judgment. In practice, this means that the study reframes artificial intelligence literacy, evaluation discipline, and decision support design as core competencies of Product Management. The policy implication of this study is to place artificial intelligence decision support within product governance structures, ensuring transparency, bias mitigation, and accountability, and in line with emerging principles for artificial intelligence-enhanced decision making (Herath Pathirannehelage et al., 2025).

Keywords: Product Management; Artificial Intelligence; Cognitive Load; Bounded Rationality; Knowledge Management; Decision Support Systems

JEL Codes: O33, M15, D83

INTRODUCTION

Product management, at its essence, is decision-oriented work. However, the information demands on product managers (PMs) have risen substantially in recent years. In the context of a single roadmap cycle, PMs must now integrate live experimentation data, customer feedback, usage data, competitor data, regulatory and security concerns, and live stakeholder feedback. These information sets are constantly changing, interconnected, and often conflicting in nature. This requires PMs to make, prioritize, and act on decisions in an environment of continuous time pressure and uncertainty.

This environment increasingly outstrips the capabilities of unaided human cognition. The problem here isn't the lack of knowledge or interest in problem-solving but the growing gulf between information-processing capabilities and decision environments. Past research indicates that information overload is related to negative effects on strain and decision quality in the context of modern workplaces (Arnold et al., 2023, https://doi.org/10.3389/fpsyg.2023.1122200). In the context of product management, it leads to slower decision prioritization and decision quality.

The latest developments in large language models (LLMs) and AI-based decision support systems offer significant hope in improving the management of these environments. In contrast to previous AI systems that were designed to support specific problem domains with data-driven analytics tools, LLM-based AI systems can aggregate data from different sources, process information, and produce decision alternatives (Handler et al., 2024, https://doi.org/10.1016/j.ijinfomgt.2024.102811). This creates a structural shift in the role of the product manager. No longer do they operate purely as decision-makers but increasingly determine the context in which information is filtered and presented to support decision-making.

This change reflects a shift to decision environment design, which is aligned with the principles of choice architecture (Thaler & Sunstein). In AI-mediated product organizations, decisions are shaped by human judgment but also by AI systems that prioritize information, organize alternatives, and reduce complexity. Productivity in product management is no longer achieved by making optimal individual decisions but by designing decision systems that facilitate sustainable judgment.

This process of change also requires a clear understanding of the role of boundaries between humans and machines. AI systems excel in decision environments with structured data and probabilistic uncertainty but are limited by their inability to handle deep or Knightian uncertainty, where probability is unknown or causal relationships are unstable or where new outcomes emerge. In these conditions of uncertainty, human judgment is critical for sensemaking, ethical judgment, and strategic interpretation of the environment. Decision productivity requires complementarity between human and artificial cognition.

With this background of information overload and different forms of uncertainty in modern product work, this article addresses the question: What is a minimum viable decision system for the product manager? How do we ensure productivity through decision systems? What role do humans play? We answer these questions by arguing that productivity is achieved by designing human-AI decision systems that augment human cognition but also maintain human control over judgment and uncertainty.

This article contributes to the field of decision productivity in the following ways: It brings together research on cognitive overload, bounded rationality, and AI-enabled decision support systems with the field of product management productivity. It offers a conceptual model of a decision system for the product manager that reframes the role of the PM as a designer of decision systems rather than a decision-maker. It provides initial empirical research on the impact of AI assistance on cognitive load and decision quality for product-related tasks.

LITERATURE REVIEW

Cognitive Limits in Knowledge Work

Herbert A. Simon's theory of bounded rationality is based on the idea that, in the presence of time, attention, and computational limitations, decision-makers tend to satisfice. In information-overloaded environments, such limitations become critical, leading to heuristics, narrow framing, and premature decisions. At the same time, cognitive load theory identifies three types of cognitive load: intrinsic, extraneous, and germane cognitive load. In the context of product managers, intrinsic cognitive load is related to the complexity of the product and the interdependencies between different parts of the product, whereas extraneous cognitive load is related to the fragmentation of tools, the constant flow of messages, and the number of metrics used.

Recent systematic studies have shown that information overload is a consequence of digitalization, leading to strain and performance decrements, including decisions, (Arnold et al., 2023, https://doi.org/10.3389/fpsyg.2023.1122200). This is especially relevant because, in the context of product organizations, information overload is often considered a problem related to the productivity of individuals, whereas, in fact, it is related to the organization of the system as a whole.

AI as Decision Support and Cognitive Augmentation

Product management can be conceived as a form of knowledge work where signals need to be synthesized into collective understanding and collective action. Product decisions are the result of the synthesis of customer understanding, technical constraints, signals from the marketplace, and organizational imperatives, each of which needs to be converted into a tangible product management artifact such as a roadmap, backlog, or prioritization rationale. As such, knowledge management (KM) is central to product governance.

Empirical research on the topic indicates that organizations are increasingly using AI, including generative AI, to support KM for sensemaking, information retrieval, and decision-making (Leoni et al., 2024; https://doi.org/10.1108/JKM-03-2024-0262).

However, other studies point to challenges associated with deploying AI for KM, such as governance, accountability, and integration with traditional decision-making processes. Other studies published in Technological Forecasting and Social Change also point to challenges such as technology-related challenges, organizational challenges, and ethical challenges as the most significant barriers to the effective integration of AI and KM (Rezaei, 2025; https://doi.org/10.1016/j.techfore.2025.124183).

The challenges associated with the effective integration of AI and KM are similar to the challenges associated with product governance.

However, a key issue that needs more research and exploration is decision provenance: the ability to track the process by which a decision was arrived at, what information was used to inform the decision, and why a particular option was selected from a set of alternatives. Decision provenance is a key issue for product management teams. Why a particular product management decision was made can often be more important than the decision itself.

While such KM systems enabled by AI can facilitate greater access to information and enhance synthesis, they can also conceal this decision paper trail. The use of generative AI, for instance, could reveal decision recommendations or synthesis results without sufficiently disclosing underlying assumptions, data, or decision pathways. The lack of transparency can hinder accountability, organizational learning, and trust in product governance processes.

While interest in AI-based KM systems is rising, existing research has devoted limited attention to how such systems can help or hinder decision provenance within ongoing product work. The relationship between AI-mediated knowledge synthesis and decision traceability has yet to be sufficiently theorized and empirically examined, particularly within contexts where product decisions are revisited, questioned, or audited over time.

In this research, we propose that AI-based knowledge management systems must be considered, not merely as efficiency enablers, but as decision traceability facilitators that connect decision inputs, processes, and outcomes. We contend that effective human-AI decision systems, such as those used in product management, must facilitate decision traceability, supporting PMs in decision reconstruction and justification while providing cognitive enhancement capabilities enabled by AI.

Research Gap

While the adoption of AI copilots by practitioners has been rapid, the literature still focuses on “PM + AI” as a tooling rather than cognition. Most research has examined AI in the context of isolated decision domains (e.g., clinical, financial, or lab settings) and not within the entire product lifecycle in which the product manager must switch between exploration, prioritization, negotiation, and execution. Thus, there is a lack of a role-level model that (i) identifies the cognitive functions that need augmentation and those that must be human-governed, (ii) explains why augmentation can be detrimental in some decision domains, and (iii) offers a model for ensuring the reliability of such augmentation. In this paper, we propose addressing this gap by considering AI in the context of product management as a cognitive architecture and governance problem rather than a capability improvement.

Theoretical Review and Conceptual Framework

Bounded Rationality and “Augmentation Layer”

Bounded rationality assumes a decrease in the quality of decisions with increasing complexity and pressure. Rather than assuming that AI overcomes Bounded Rationality, we conceptualize AI as an augmentation layer that has the potential to enhance search and evaluation capabilities by reducing extraneous information (noise filtering), condensing information (summarization), and allowing inexpensive counterfactual exploration (scenario generation). This conceptualization also fits with a conceptualization that assumes that organizational reliance on AI fundamentally changes Bounded Rationality and requires new leadership approaches (Shick, 2024, https://doi.org/10.1108/DLO-02-2023-0048).

Cognitive Load and Decision Fatigue in Product Work

Decision fatigue in product management may be conceived as a cognitive depletion effect due to repeated exposure to high-uncertainty trade-offs in both the discovery and delivery phases of product work. PMs must make sense of incomplete information sets, balance conflicting demands from stakeholders, and commit to irreversible or costly decisions within constrained timeframes. Ultimately, this repeated cognitive activity results in decision fatigue and cognitive depletion, which is consistent with research on cognitive load and decision fatigue in knowledge work.

Artificial intelligence is often proposed as a potential solution to decision fatigue in product management by automating analytical work. In theory, this is true: artificial intelligence may synthesize information sets, reveal patterns, and generate structured decision sets to minimize the cognitive effort required to make decisions. However, artificial intelligence may also increase cognitive load when its recommendations are of poor quality, inconsistent, or not well-calibrated to the decision task at hand. Under these conditions, PMs must invest additional cognitive effort to correct or validate artificial intelligence recommendations.

We refer to this condition as the verification trap: when the cognitive effort required to fact-check, de-bias, or reconstruct an artificial intelligence recommendation is greater than the cognitive effort required to produce the recommendation in the first place, the augmentation layer is no longer cognitively beneficial. Artificial intelligence does not alleviate decision fatigue but instead redistributes cognitive effort from creation to verification, which may involve sustained attention and error detection mechanisms that are cognitively costly.

This phenomenon can be further elucidated in terms of the concept of dual-process theory proposed by Kahneman. In particular, System 1 thinking can be characterized as rapid, intuitive, and associative thinking and plays a significant role in activities like vision-setting, negotiation with stakeholders, and making context-based judgments. On the other hand, System 2 thinking can be characterized as slow, analytical, and effortful thinking and plays a significant role in activities like structured evaluation, tradeoff analysis, and error detection. In the case of product work, there is a continuous requirement to switch between these two thinking systems, leading to cognitive strain.

In terms of the role of AI systems in the context of PM activities, it can be seen that AI systems should be positioned in the role of System 2 supports in activities like analytical synthesis, option generation, and structured reasoning. In particular, when AI systems function properly, they should be able to reduce the workload of PMs in activities like structured evaluation and tradeoff analysis, allowing them to use their System 1 thinking for activities like vision-setting, negotiation with stakeholders, and context-based judgments. However, when AI systems fail to function properly in terms of reliability and transparency, PMs would be forced to use their System 2 thinking to verify and correct the errors in AI system outputs while at the same time being required to use their System 1 thinking for activities like vision-setting and negotiation with stakeholders. This would lead to decision fatigue.

In terms of productivity implications, it can be seen that the key issue with AI systems in the context of PM activities is not their use but their ability to reduce the net cognitive load of PMs. In particular, AI systems that fail to demonstrate reliability, transparency, and context-based alignment would trigger the verification trap and fail to provide the expected benefits to PMs. In particular, in the context of developing effective decision systems involving AI systems and PMs, it would be important to minimize the requirement for verification to enable PMs to use their analytical thinking while at the same time being able to use their intuitive thinking for activities like product work.

Conceptual Framework

As depicted in Figure 1 below, the proposed conceptual framework is as follows: product complexity is theorized to increase cognitive load by increasing the volume, interdependence, and uncertainty of decision inputs. As cognitive load increases, decision quality and effectiveness are theorized to deteriorate. However, this negative relationship is mitigated by the proposed intervention of AI decision support systems that augment human cognitive abilities. As such, decision quality and effectiveness are theorized to improve when cognitive load is mitigated by AI decision support systems. However, this relationship is conditional on the proposed design requirement of cognitive augmentation being embedded in the decision system and not being an ad hoc feature of the system.

The proposed framework also includes a governance filter in the relationship between decision support systems and decision quality. This is to ensure that decision support systems do not increase coordination costs and confuse responsibility for decision outcomes. As such, decision support systems are theorized to improve decision quality and effectiveness only when a governance filter is embedded in the system. The governance filter includes decision provenance, decision support system transparency, decision support system alignment to organizational values, and the PM's authority to override decision support system recommendations.

This is a self-consciously circular rather than a linear process. The decisions that emerge through the human-AI system have outcomes that, in turn, update the cognitive state of the PM and the decision environment of the AI. The outcomes of decisions will eventually feed back into the process of calibrating trust and governing the AI, and using the AI. This process will eventually allow for a type of learning, both at the individual and the system level, that will impact the use of the AI over the course of decision-making.

Decision effectiveness and decision quality within this model are not ends but rather means to influence decision environments. Product governance structures will influence the ways in which learning is captured and decisions are rationalized. The model situates PMs as decision-makers but also as designers of decision systems.

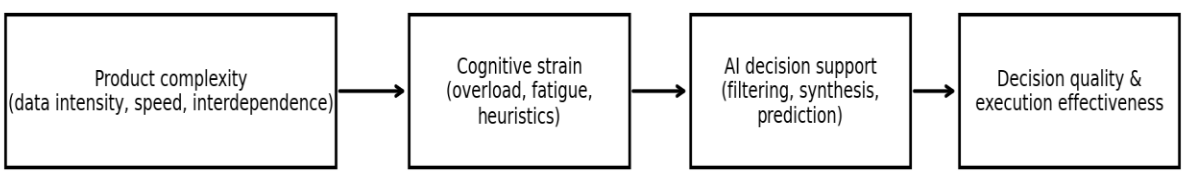

Figure 1: Conceptual Framework of AI as A Cognitive Augmentation Layer in Product Management

MATERIALS AND METHODS

The research design used in this study is descriptive and explanatory. In the first place, a structured synthesis of the pertinent literature on bounded rationality, cognitive overload, decision support systems, and AI-enabled knowledge management (2019-2025) was conducted. Second, pilot empirical data were collected from an online survey of practicing product managers in technology-driven organizations (n=174). In the second place, the measures included cognitive overload, decision fatigue, prioritization clarity, cycle time, and confidence in strategic trade-offs. In addition, the study included a comparison between those who reported routine use of AI decision support tools such as AI summarization tools, analytics copilots, and LLM-enabled ideation and those who did not.

FINDINGS

Overall, the sample of PMs consistently described the contemporary product management (PM) task as one of "signal compression," or dealing with too many inputs, not enough time, and increased reliance on cross-functional alignment. For those without routine AI support, the experience was one of increased pressure and confusion in prioritization. For those with routine AI support, the benefits were reported to be largely in the areas of evidence triage (compressing feedback, research, and meeting notes), pattern recognition (grouping qualitative inputs), and scenario exploration (drafting options and trade-offs). Notably, both groups emphasized that the quality of AI outputs is critical to whether they help or exacerbate the problem. Characteristics of the respondents are shown in Table 1. Table 2 shows the differences in the presence of the cognitive and execution factors for the AI-augmented and non-AI workflows on a 1 to 5 Likert scale, where higher numbers indicate the presence of the construct. The findings suggest that the AI-augmented group experienced lower overload and fatigue, and higher clarity and confidence.

Table 1. Sample Characteristics (Pilot Survey, N=174).

Characteristic	Category	Count	Percent
Industry	SaaS/Software	88	51%
Industry	FinTech/Payments	26	15%
Industry	Consumer Tech	32	18%
Industry	Other	28	16%
Experience	0-3 years	34	20%
Experience	4-7 years	71	41%
Experience	8+ years	69	40%
AI use	Routine AI decision support	96	55%
AI use	Non-routine/no AI support	78	45%

Table 2. Group Comparison of Self-Reported Cognitive and Execution Indicators (Pilot Survey)

Outcome (1-5)	Non-AI Mean	AI Mean	Mean diff	t (df)	p-value
Cognitive overload	4.2	3.4	-0.8	6.1 (172)	<0.001
Decision fatigue	4.0	3.3	-0.7	5.4 (172)	<0.001
Prioritization clarity	2.7	3.6	0.9	-6.8 (172)	<0.001
Decision confidence	2.9	3.7	0.8	-6.0 (172)	<0.001
Execution cycle speed	2.8	3.4	0.6	-4.1 (172)	<0.001

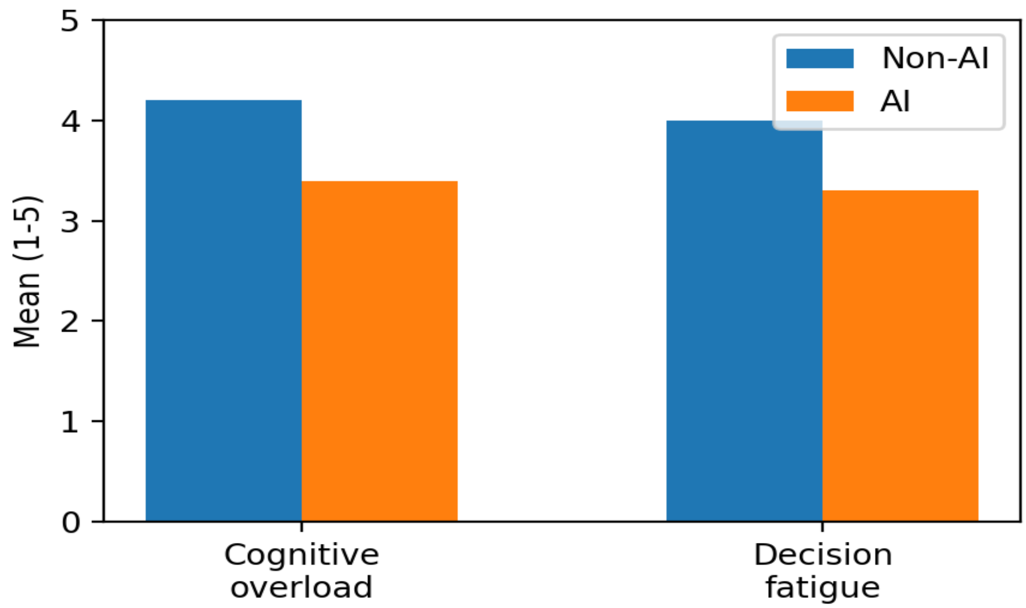

Figure 2: Mean Cognitive Strain Indicators by Workflow Group (Pilot Survey)

Conclusion and Recommendations

This research recasts the use of AI in product management as a cognitive necessity rather than a choice for augmenting productivity. As product management becomes more and more information-saturated, the relevant limit is no longer the availability of data but the ability to interpret that data into a clear and accountable decision. Our literature review and pilot research suggest that decision support systems can reduce cognitive load and improve the clarity of decision priorities, but that these benefits depend on the intentional integration of the AI tool into the product management workflow. The general literature on human-AI interaction also suggests that decision tasks are particularly vulnerable to coordination loss if the human is unable to calibrate when to use the AI tool or when accountability is unclear (Vaccaro et al., 2024, https://doi.org/10.1038/s41562-024-02024-1). Ultimately, the relevant question is not whether product managers should use AI systems, but what decision system product managers operate within and how that system can be made more reliable.

Recommendations for Practice

(1) Use AI as a decision support layer, rather than an oracle, with well-defined roles such as triage, synthesis, and generation of alternatives. (2) Embed evaluation discipline into the product process, such as requiring evidence summaries that are traceable to the source, maintaining a decision log, and performing periodic "AI output audits" to check for accuracy and bias. (3) Consider PM AI literacy as a governance capability, which includes prompt design, model limitations, and risk detection. These considerations are in line with the design principles for AI-augmented decision-making systems, which have recently emerged in the literature (Herath Pathirannehelage et al., 2025, https://doi.org/10.1080/0960085X.2024.2330402).

Recommendations for Organizations and Policies

AI decision support should be embedded into the product governance process, where accountability is clear. For instance, major roadmap decisions should require the synthesis of human rationale and AI-assisted evidence synthesis. At the organizational level, the AI-KM literature suggests that the major barriers to AI adoption are organizational and ethical, rather than purely technological (Rezaei, 2025, https://doi.org/10.1016/j.techfore.2025.124183). Therefore, organizational policies should address data provenance, privacy, IP, and human override rights.

Limitations and Future Research

This paper's pilot survey is self-reported, cross-sectional, and cannot establish causality. Future studies should use longitudinal designs, instrumented workflow analysis, and task-level experiments that reflect the decision-making contexts of PMs. This research, when conducted rigorously, can help move the field beyond the hype and into design, where the conditions under which AI improves, worsens, and can be leveraged by PMs to lead in the AI era can be determined.

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