

Human–AI Collaboration in Product Management: A Systematic Review of AI-Augmented Decision-Making Across the Product Lifecycle

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Abstract

Artificial Intelligence (AI) is gradually changing the landscape of product management by improving how PMs gather, process, and evaluate data and options to manage products across their lifecycle. This review explores the new paradigm of Human-AI collaboration in the product management domain and looks at how AI functions effectively on the side of the product manager. It merges a variety of machine learning, predictive analytics, NLP, recommender systems, generative AI, and emerging agentic AI applications in customer and market discovery, product ideation, strategy and prioritization, road mapping, product development, product launch, and post-launch optimization. Specific focus is placed on task distribution, responsibilities and decision-making power between product manager and AI system. The study suggests that AI can offer many benefits in areas such as data analysis, pattern recognition, prediction, information synthesis, content creation, recommendations, and automation, while human involvement is still crucial for aspects of context interpretation, strategic decision-making, creativity, empathy, ethical considerations, and accountability. Yet, collaboration is hindered by issues such as algorithmic bias, hallucination, opacity, automation bias, over-reliance, privacy issues, deskilling and unclear accountability. The review thus suggests a framework of integration between product lifecycle activities, AI capabilities, human expertise, collaboration mechanisms, governance and organizational outcomes. The framework also emphasizes how product managers will be moving away from AI-enabled product management and toward agentic systems where product managers will take on more supervisory, orchestrating, evaluating and governing roles. Lastly, the review pinpoints research priorities related to human-AI task allocation, trust calibration, autonomous agents, measurement of collaboration, responsible AI, and end-to-end empirical evaluation.

Keywords: Artificial Intelligence, Human–AI Collaboration, Product Management, AI-Augmented Decision-Making, Generative AI, Agentic AI, Decision-Making, Product Lifecycle, AI Governance.

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I. Introduction

The use of artificial intelligence (AI) in knowledge-intensive managerial activities is growing, changing the way knowledge is gathered, alternatives evaluated and

decisions made [1]. The use of machine learning, predictive analytics, natural language processing (NLP), recommender systems and generative AI has increased the capabilities of intelligent systems to handle massive amounts of complex data, uncover patterns, derive

insights, and facilitate managerial activities. Recently, AI agents have been added to this list, with the ability to handle complex tasks, and to perform multi-step tasks with increasing autonomy [2]. As a result, AI is moving away from being a technology that automates tasks and is becoming more of a tool to augment decisions where computational power is added to, but not a substitute for, human intelligence. The research on human–AI teaming also highlights a need to actively design human–AI collaboration to achieve the best results, not to let AI be a substitute for human decision-makers.

Product management is an especially relevant lens for understanding product change, as it can be seen as a decision-making context for the organization [3]. Product managers constantly make and/or coordinate decisions related to customer needs, market opportunities, product strategy, prioritization of features, allocation of resources, road mapping, product development and performance evaluation. These choices are made in an environment of uncertainty and often involve the integration of data from different customers, market, competitor, technical and organizational stakeholders. AI can enhance these activities by providing customer and market analysis, demand forecasting, recommendation, information synthesis and content generation [4]. Product-management decisions are not simply a matter of optimization, though. They also need experience, intuition, creativity, context interpretation, strategic thinking and awareness of organizational limitations. As a result, the role of AI in product management becomes more about data-driven decision making and managerial expertise.

In this context, Human–AI collaboration means the coordinated interactions between product managers and AI systems, where the responsibilities, information, and decision authority are shared based on their respective capabilities [5]. This can be differentiated on a spectrum from AI automation where systems carry out preprogrammed tasks, to AI assistance where systems provide information or recommendations, to AI-augmented decision-making where AI actively supports human evaluations, to human–AI collaboration, in which humans and AI work together with each other in an iterative process to achieve common goals, and finally to increasingly autonomous AI agents that can now perform series of actions with limited human involvement. Effective human–AI teaming has recently been defined as being complementary, with AI providing speed, scalability, pattern recognition, and computational analysis, while humans provide contextual understanding, ethical reasoning, creativity, and accountability [1]. So the question is not about whether decisions should be made by humans or AI, but rather, how can decision authority and decision responsibility be designed to lead to effective and responsible collaborative decision making?

Figure 1 illustrates the conceptual scope of the review by positioning Human–AI collaboration as the mechanism through which AI capabilities and managerial expertise jointly support decision-making throughout the product lifecycle.

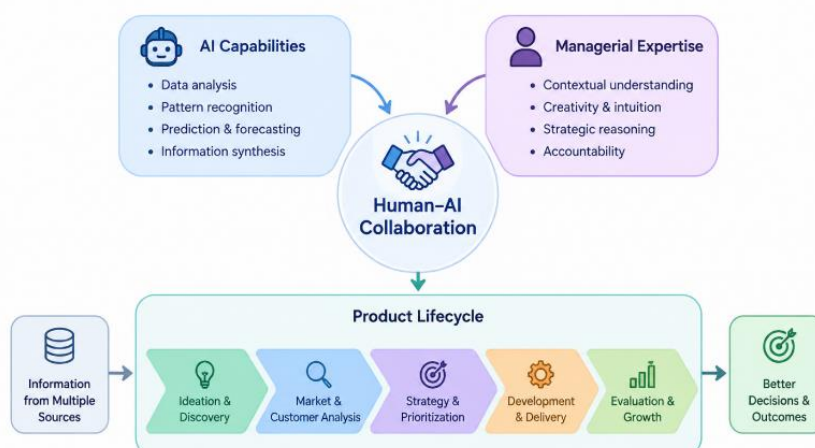


Fig. 1. Conceptual Scope of Human–AI Collaboration in Product Management

While there is a growing interest in AI for product management, there is a scattered literature in technology, decision type and product life cycle [6]. Past work tends to focus on uses such as customer analytics, recommendation systems, forecasting, generative AI, or AI as an assistant for product management, but rarely integrates how humans and AI work together to make product-management decisions. Additionally, there has been a lack of synthesis of key organizational and behavioral challenges that arise within the product-management context, such as issues of trust, explainability, accountability, algorithmic bias, automation bias, and over-reliance. Research in wider research on Human–AI collaboration shows that control of the decision-making process, calibration of trust in the AI, and an explanation that is well designed can significantly affect the way users interact with the AI recommendations. As AI systems become more independent and start to impact various interdependent product decisions, these become even more significant.

The review adds value by bringing together disjointed research concerning the use of AI in product management, summarizing the scope of AI applications throughout the product lifecycle, analyzing the division of labor between humans and AI and decision rights, and identifying the key dimensions of collaboration and associated risks. It also explores the shift from traditional AI support to more agentic systems and proposes a framework for conceptualizing Human–AI collaboration in product management. Last, future research directions are highlighted with regard to governance, trust, explainability, accountability, autonomy and the emerging role of product manager as a strategic actor.

II. Literature Search and Review Method

A. Literature Search Strategy

A formal literature search was performed to locate scholarly research related to the artificial intelligence (AI), product management, decision making and the Human–AI collaboration. Literature searching was conducted by using the most important academic databases such as Scopus, Web of Science, IEEE Xplore, ACM Digital Library, ScienceDirect and SpringerLink. The search was conducted to capture the evolution of AI-powered product-management practices, with a special focus on recent developments in generative AI and agentic systems. Search terms were generated based on

the key concepts of the review and then Boolean operators were used to create a combination of these terms. Some of the key terms identified were: “human-AI collaboration”, “product management”, “artificial intelligence”, “decision-making”, “product lifecycle”, “generative AI”, “machine learning”, “AI agents”, and “product development”. These combinations were employed to identify research to be included: human-AI collaboration AND product management, artificial intelligence AND product decision-making, and generative AI AND product development.

B. Selection and Relevance Criteria

Studies retrieved were screened based on their relevance to the aims of the review. Peer-reviewed journal articles, conference papers, and high-quality scholarly publications were prioritized that explored the use of AI in product management, product development, and/or decisions-making related to these fields. Studies that covered product-management decisions or product lifecycle activities, human involvement, and the relationship between the manager and the intelligent systems were found to be relevant. Literature pertaining to customer analytics, forecasting, recommendation, product strategy, prioritization, product development support, autonomous/agentic AI or generative AI was also included, if it contained information useful to the understanding of product management decision making. Only studies that had direct relevance to the product-management activities and human decision processes were included, and studies that only addressed technical aspects of the development of AI models were not included. Records and publications that were duplicated that lacked adequate relevance and/or scholarly quality were also eliminated during screening.

C. Literature Classification and Synthesis

The sources selected were classified thematically to make a systematic comparison between the studies. The studies were analyzed based on the product lifecycle stage, type of AI technology, AI function, human involvement, level of decision making, collaboration mode, outcomes, risks, and governance. The classification helped the review identify trends in a sometimes-disjointed research landscape, as well as differentiate between various types of Humans–AI collaboration, ranging from assistive, interactive to human-in-the-loop, supervisory, and increasingly

autonomous. The synthesis then explored how AI can have an analytical, predictive, and generative and automation role, with human actors having different levels of interpretation, evaluation, strategic judgment and accountability.

Each literature was grouped based on the dimensions shown in Table 1, allowing comparisons of the AI functions, responsibilities of humans, types of decision-making process, and collaboration process used in various product-management activities.

TABLE I. LITERATURE CLASSIFICATION FRAMEWORK

Dimension	Categories
Lifecycle stage	Discovery, strategy, development, launch, post-launch
AI technology	ML, NLP, GenAI, recommender systems, AI agents
AI function	Prediction, analysis, generation, recommendation, automation
Human role	Decision-maker, evaluator, supervisor, collaborator
Decision level	Strategic, tactical, operational
Collaboration mode	Assistive, interactive, human-in-loop, supervisory
Outcome	Efficiency, quality, innovation, product performance
Risk	Bias, opacity, over-reliance, hallucination, accountability



Fig. 2. Literature Search and Selection Process

Figure 2 outlines the overall review process, starting with Literature Identification, Initial Screening, Relevance Assessment, Full-Text Evaluation, to Literature Set, and finally to Thematic Synthesis. This process offers a clear view of the identification and structuring of relevant studies and does not need to be overly procedural, as this detracts from the value of the review: the synthesis of knowledge on Human–AI collaboration in product management.

III. Foundations of Human–AI Collaboration and AI-Augmented Decision-Making

A. Human–AI Collaboration in Product Management

Human–AI collaboration in product management is the strategic partnership between humans and artificial intelligence to achieve product management goals and make decisions. This is not just about the use of AI

software as it is a dynamic process, continuing interaction, exchange of information, feedback, evaluation and adjustment between human and computational actors. Usually, when a user is using conventional software, he/she uses a tool to do a software-defined task. In contrast, in Human–AI collaboration, AI can analyze information, generate alternatives, make recommendations and respond back to human feedback, and product managers interpret the outputs and decide how they should impact product decisions. This means that there is a collaborative relationship, where responsibilities can be different depending on the nature of the task, information available and required level of judgment [7].

Collaboration is of particular concern for product managers, since in many cases, there is incomplete information, completing goals, and uncertainty in product decisions. AI can offer computational and analytical support while product managers offer context for the organization, customer understanding, strategic direction, and accountability. The effectiveness of this relationship, thus, relies on the distribution of information, authority and responsibilities between the human and AI components.

B. AI-Augmented Decision-Making

The term AI-augmented decision making refers to the application of AI to enhance, but not necessarily supplant, human decision-making. For example, AI systems can analyze large amounts of data, find patterns, make predictions, suggest alternatives, optimize resources, come up with product ideas and do scenario analysis. AI can identify new customer needs, predict the demand for a product feature, and priorities features based on their projected value, or even come up with alternate product ideas, to cite only a few examples. These capabilities can help ease information processing loads and increase the opportunities product managers have for alternatives [8].

Importantly, AI augmentation doesn't mean that decision-making power is being given to the AI system. In a lot of product-management scenarios, AI provides

evidence, recommendations, or alternatives, but the product manager is still on the hook to evaluate their pertinence and decide which to pursue. This is especially beneficial in situations where strategic choices are made that require balancing various factors, such as customer needs that may be unclear, ethical concerns, or organizational limitations, and where these factors can't be fully captured in data.

C. Complementarity Between Human and AI Capabilities

1) AI Capabilities

Advantages of AI systems are fast response, large scale, computational processing power, pattern recognition, prediction, information synthesis, and generation. They can handle a lot of data and find patterns that might not be obvious to people. Generative AI also can create content such as text, concepts, summaries, alternatives and other content that supports decision-making [9].

2) Human Capabilities

Product managers bring in assets that are hard to codify computationally, such as strategic thinking, understanding, empathy for customers, creativity, ethical decision making, managing stakeholders, and taking accountability. Human decision-makers can explain fuzzy situations, comprehend organizational politics, accommodate conflicting interests and think about consequences which might not be manifested in historical information [10].

3) Complementary Intelligence

These abilities can be integrated to form the concept of complementary intelligence, where AI augments the information, predictions and alternatives that a human decision-maker is able to access, with human making the interpretation, judgment and taking the responsibility for decision. The goal is not necessarily to replace the role of AI, but to build out decision arrangements where each actor does activities that leverage its comparative strengths [11].

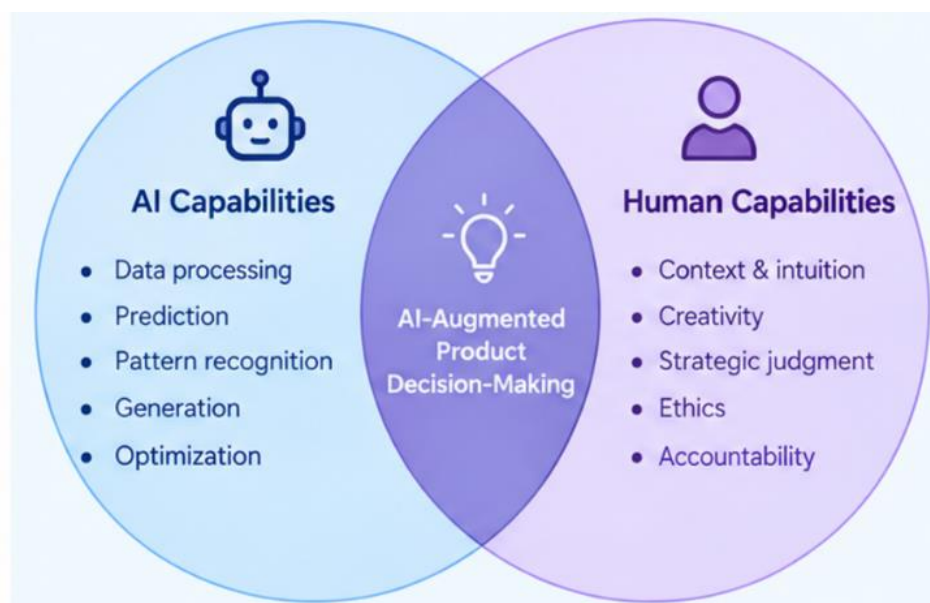


Fig. 3. Human–AI Capability Complementarity

Figure 3. illustrates this relationship by positioning AI strength data processing, prediction, pattern recognition, generation, and optimization—alongside human strengths such as context, creativity, strategic judgment, ethics, and accountability. Their intersection represents AI-Augmented Product Decision-Making.

D. Models of Human–AI Task Allocation

There is a continuum of human-AI collaboration that can be modeled as task allocation. AI provides information and recommendations in human-led decision-making, with the product manager holding the decision-making power. The product manager reviews and filters the recommendations, predictions or rankings made by the AI. Human-in-the-loop collaboration involves humans deciding in the same loop that data and algorithms are used in, with their output being checked, corrected, or modified before actions are taken that have consequences [12].

On a higher level of AI autonomy, human-on-the-loop supervision means that the AI completes a larger percentage of activities with human oversight and directions, if needed, to ensure results. The new trend of agentic AI collaboration takes it one step further. Increasingly, agentic systems can execute multi-step tasks that require planning, reasoning, use of tools,

execution and monitoring. In the context of product management, this might help AI systems to orchestrate interconnected tasks between research, analysis, prioritization, development assistance, and performance monitoring. With greater autonomy comes greater responsibility for correct human supervision, decision limits, accountability, and governance, however.

IV. Human–AI Collaboration Across the Product Lifecycle

AI is gradually becoming a key part of the product management process from customer needs identification to post-launch product optimization. AI can not only perform one-off analytical tasks, but it can also engage in various interconnected tasks that involve data processing, generating insights, predicting outcomes, suggesting alternatives, and automating repetitive tasks. But the type of collaboration varies with the context of the decision. While AI is useful for large-scale data processing, pattern recognition and predicting and generating alternatives, product managers are crucial for interpreting the context, making strategic decisions, being creative, coordinating stakeholders and taking accountability [13]. Therefore, Human–AI collaboration can be seen as a decision-making process running across the whole lifecycle, where the role of AI and human beings is continuously integrated.



Fig. 4. AI-Augmented Decision-Making Across the Product Lifecycle

Figure 4 presents the central lifecycle perspective adopted in this review. It maps eight stages—Customer/Market Discovery → Product Ideation → Product Strategy → Feature Prioritization → Roadmap Planning → Product Development → Product Launch → Post-Launch Optimization—and identifies the AI contribution, human contribution, and resulting joint decision at each stage.

A. Customer and Market Discovery

1) AI-Based Customer Insight Generation

Customer and market discovery is the information that is used to inform product decisions. By leveraging AI, product teams can sift through vast amounts of customer data from reviews, surveys, support chats, social media, behavioral patterns, and more, transforming this customer feedback into actionable insights. Natural language processing can detect sentiment, help uncover consistent themes, customer complaints, and new topics, and machine-learning technologies can be used for customer segmentation and behavioral analysis. These features enable product managers to leverage small samples of manual reviews and evolve to a continuous and large-scale generation of customer insights [14].

2) Human interpretation of AI-Generated Insights

However, with all these capabilities comes the need for human interpretation of AI-generated insights. The detection of negative sentiment does not necessarily mean that there is a product defect, it could be a matter of a temporary market event, a particular customer group or something completely different. It is important for

product managers to process the analytical results based on the customer environment, the business goals, the competition and priorities in the organization [15]. Human judgment translates statistical patterns into products implications.

3) Benefits and Limitations

The key advantages to discovery using AI are scale, speed, consistency and continuous analysis. But, as with any other system, AI tools are limited by the data they use. Poorly constructed data sets can lead to misleading customer information and correlations can be mistaken for causal relationships. However, human input plays a crucial role in verifying that the AI-generated patterns reflect customer requirements and market realities.

B. Product Discovery and Ideation

1) AI-Supported Opportunity Identification

AI can help predict future product trends, recurring customer problems, market gaps, and unmet needs to expand the product discovery. AI can draw insights from customer feedback, market and behavioral data to identify opportunities that may not be apparent to a human. This will open up more opportunity space for product teams [16].

2) Generative AI for Product Ideation

Generative AI also enhances this function by generating alternative product concepts, user scenarios and personas, feature ideas and potential solutions. Unlike analytical systems, generative systems can be involved in the process of developing potential product

alternatives. The output can be used by product managers to give them a head start in brainstorming and to examine more options in less time.

3) Human Creativity and Idea Evaluation.

AI generated ideas, however, shouldn't be confused with a product opportunity that has been validated. Product managers need to evaluate each concept against the criteria of desirability, feasibility, strategic fit, differentiation, customer value and commercial potential. Human creativity is still vital for identifying and leveraging new opportunities, as well as merging AI-provided options with organizational expertise. AI can then help to broaden the scope of ideation, with human input filtering down to those ideas that warrant further exploration [17].

C. Product Strategy and Market Decisions

1) AI-Supported Market Intelligence

Strategically speaking, AI can assist with market intelligence on a continuous basis and keep track of competitors, analyze industry trends, monitor customer behavior and assess pricing information. Automation of this analysis can help save time and effort in gathering and compiling market data, allowing product managers to gain a more up-to-date understanding of the competitive landscape [18].

2) Predictive Decision Support

Predictive AI can also be useful in strategic planning by predicting market growth, customer adoption, revenue and churn, and demand. A variety of scenarios can be created to gain estimates on the future outcome of the choices made. These forecasts can help inform strategic conversations, especially if the historical data available is informative.

3) Human Strategic Judgment

However, predictive accuracy does not necessarily convey strategic value. Product managers need to consider the goals of the organization, the risk appetite, resource limitations, competitiveness, and strategic future considerations. A forecast could suggest that a specific market is right for a company, yet strategic factors could indicate that the company would be better off doing without the market. We need to think about using AI to inform our strategic decisions, not make them.

D. Feature Prioritization and Backlog Management

1) AI-Based Feature Ranking

AI can also aid in decision-making processes when it comes to prioritization. When considering all the above data, AI systems can prioritize features based on their likely usability, development time, and expected value to the business [19]. Ranking can be useful for product managers in dealing with large backlogs that can help narrow in on features that warrant more in-depth analysis.

2) AI-Supported Requirements Analysis

AI can also use the requirements to classify and group similar requirements, identify duplicate requests, consolidate customer requirements and create initial user stories. These capabilities diminish repetitive analytical and documentation tasks and aid product teams to organize intricate collections of inputs from customers and stakeholders.

3) Human Validation and Trade-Offs

The fundamental basis of feature ranking is the judgment made by human beings to make trade-offs. Customer value, technical feasibility, development cost, strategic value, dependencies, time constraints, organizational priorities are all factors product managers have to consider when balancing. An AI system can prioritize a much sought after feature over another feature, but the product manager can have a valid reason for choosing the lower of the two features as it can fulfil a key strategic goal. In such instances, where competing aims are not easily reduced to a simple computation, human validation is essential and will continue to be so.

E. Product Roadmap Planning

1) AI-Based Scenario Generation

All product decisions need to be made in a sequence and at the right time for roadmap planning. AI can help to create different release timelines, feature combinations, resource setups and market scenarios. AI can analysis several possibilities to provide product managers with insights into the implications of different roadmap approaches [20].

2) Dynamic Roadmap Adaptation

AI-powered roadmaps can be updated on an ongoing basis, which is not possible with traditional planning methods. Assumptions may need to be reconsidered due to changes in customer behavior, market conditions, product performance, progress in product development, or changes in the availability of resources. AI can detect these shifts and make possible suggestions to improve the plan for easier adaptation.

3) Human control over strategic priorities

This flexibility should not, however, compromise the necessity for human strategic control of key decisions in the roadmap. Roadmaps help to convey an organization's priorities to engineering, marketing, sales, leadership and other stakeholder groups. Product managers must therefore consider not only predicted outcomes but also organizational commitments, dependencies, stakeholder expectations, and long-term product vision. AI can make roadmap planning more responsive, but strategic ownership remains a human responsibility.

F. Product Development and Execution

1) AI-Assisted Requirements and Documentation

AI can assist in the product requirements to user stories, product requirements, acceptance criteria, technical documentation, and more during the development phase. Generative systems can provide summarization of requirements and may be used to translate information from one representation to another, which can help to reduce communication and documentation loads [21].

2) Generative AI (Artificial Intelligence) and Software Development

AI has also been used in software-based product development, thanks to generative AI. Systems can help produce code, create tests, debug, explain and review codes. All can help to speed up implementation and give development teams the opportunity to try out different technical solutions earlier. This can translate to improved productivity for product managers as it brings validated product concepts to life faster.

3) Human Supervision and Validation.

But AI-driven development artifacts do need to be suitably reviewed by humans. Product managers need to make sure that the requirements generated are consistent with the problem that is to be solved by the customer and

the goals that are to be achieved by the product. In addition, engineering teams must be engaged to validate technical feasibility, quality, security and maintainability. AI brings in speed of execution and generation while humans retain the accountability of making sure it is implemented in the best way to meet the product intentions.

G. Product Launch and Go-to-Market

1) AI-Based Customer Segmentation and Targeting

AI can assist with product launches in various ways, such as market segmentation, audience identification, personalization, and targeting. Customer information can be used to segment customers into different categories that have different needs, or different predicted responses to specific product propositions. This will enable a more focused go-to-market strategy for marketing and product teams [22].

2) Generative AI for Product Communication

In addition, Generative AI can help with product descriptions, communications options, campaign ideas, positioning statements, and much more. Brainstorming alternatives is a fast process that helps teams to consider alternative modes or approaches to communicating product value and adjusting messages to various audiences.

3) Human Oversight

However, human oversight is still essential as there is more involved in effective product communication than optimization for engagement. Product managers and marketing teams should get consistency with the brand identity, ethical communication principles, culture and strategic positioning of the product. When it comes to AI-generated content that might overhype product attributes, make up false claims or miss cultural considerations, human judgment plays a crucial role.

H. Post-Launch Evaluation and Optimization

1) AI-Based Product Performance Monitoring

Once it is launched, AI can continuously monitor the performance of the product. These systems can look at customer usage patterns and identify anomalies, predict customer churn rates, and measure changes in customer

satisfaction, using machine learning. This establishes a continuous feedback loop to detect issues or opportunities in the product teams [23].

2) Continuous Customer Feedback Analysis

AI can also automate the continuous integration of reviews, complaints, support interactions, behavior and measures of performance. The feedback received after a product launch should not necessarily be a one-off research exercise – it can be a continuous snapshot of the customer experience, with AI helping to build a more dynamic picture. This can speed up the process of determining recurring issues and new requirements.

3) Human Decision-Making for Product Iteration

The final one does, however, involve human product judgment. Product managers need to decide what to change, who to prioritize for changes, whether a feature should be altered or removed, and how new issues should affect the overall product plan. While the signals may be picked up and consequences forecasted by AI, the right product response will depend on customer value, business goals, feasibility and product direction.

TABLE II. AI CONTRIBUTIONS AND HUMAN RESPONSIBILITIES ACROSS THE PRODUCT LIFECYCLE

Lifecycle Stage	AI Contribution	Human Contribution	Resulting Decision
Customer discovery	Data and sentiment analysis	Contextual interpretation	Customer insights
Ideation	Idea generation	Creative evaluation	Product concepts
Strategy	Forecasting and market intelligence	Strategic judgment	Product strategy
Prioritization	Feature ranking	Trade-off assessment	Feature priorities
Road mapping	Scenario generation	Resource and priority decisions	Product roadmap
Development	Generation and automation	Validation and supervision	Product implementation
Launch	Targeting and content generation	Brand and market judgment	Go-to-market
Post-launch	Monitoring and prediction	Product interpretation	Product optimization

Table 2 combines the responsibility distribution for the product lifecycle. The pattern shows that the more that AI is involved, the faster, larger, more in-depth and more extensive the number of alternatives will be, and the greater the human involvement in interpreting, choosing strategy, evaluating context and in accountability. Importantly, these roles are not distinct and separate.

With the increasing capabilities and autonomy of AI, some actions could shift from being executed by humans to assisted or supervised by AI. While this life cycle approach suggests a trade-off between human or AI control, however, it clearly shows that the best Human – AI collaboration is seen as a dynamic distribution of the decision responsibility based on the nature of the task,

the ability of the AI, the uncertainty of the task, and the consequences of error.

V. Dimensions, Outcomes, and Challenges of Human–AI Collaboration

The value of AI in product management is not just about technology but also about how AI systems and product managers interact, share responsibility and have decision-making power. While AI can boost analytical ability, suggest alternatives, and automate repetitive tasks, these advantages vary based on factors like task characteristics, trust, explainability, human expertise, and interaction quality. Meanwhile, there are risks associated with AI-influenced decision-making, such as bias, reliability, accountability, privacy, over-reliance, and readiness of the organization. This section brings together these dimensions to look at the implications for product-management outcomes.

A. Dimensions of Effective Human–AI Collaboration

1) Appropriate Task Allocation

To collaborate effectively, tasks need to be distributed based on the strengths and weaknesses of humans and AI. In general, AI is suitable for tasks that require massive volumes of data to be processed, patterns to be recognized, predictions to be made, classifications to be performed and repetitive analysis to be conducted. The more uncertain the task, the more ambiguous the goal, the more complex the trade-offs or the more serious the consequences for getting it wrong, the more people are involved. Thus, when allocating tasks, it is important to consider the reliability of AI tools, the complexity of the task, uncertainty, the risk of error, and the amount of human judgment needed. Product organizations can split individual decisions into analytical and judgmental tasks, instead of splitting an activity into its entirety between humans and AI [24].

2) Trust and Trust Calibration

The level of trust is a key factor in the successful application of AI recommendations by product managers. Calibrated trust is fundamental to effective collaboration, where the user will trust an AI when it is likely to be accurate, and is cautious when it may be unreliable or have significant limitations. Overreliance can result in automation bias, where product managers rely on AI suggestions without careful consideration. On the other hand, a level of distrust to the extent that it can

hinder the benefits of AI-driven analysis. Too much distrust can inhibit the benefits of AI analysis, however. Trust should then be built on experience, performance-based feedback, transparency and understanding of the capabilities of the system [25].

3) Explainability and Transparency

Explainability is especially crucial when decisions about products are consequential and they are made based on AI output. Product managers might want to know how a recommendation came about, what information led to this recommendation, and what uncertainties or limitations exist about the result of the recommendation. An AI system with transparency can help in making a meaningful evaluation by separating out strong evidence and uncertain predictions. Explainability is thus not just a requirement for the technology but also a key part of the quality of the managerial decisions, as it allows the product manager to question, validate or invalidate suggestions from AI.

4) Human Expertise and Domain Knowledge

Product-management skills are still very much needed, since there are many decisions that just can't be made based on numbers alone. Product managers grasp the contexts, limitations, expectations and needs of customers, stakeholders, competition, and strategy goals. With domain knowledge managers can determine if an AI recommendation would seem promising but is not feasible or desirable due to longer-term product plans. This means that human understanding serves as an intermediary step between the information that AI outputs and what an organization does.

5) Communication and Interaction

The quality of human-AI interaction also influences human-AI collaboration. Conversational systems and generative systems allow for a cycle of prompting, questioning, correcting, refining, and validating to take place by the product manager in an iterative manner. With effective interaction, AI becomes a dynamic decision-making partner instead of a mere source of information. The usefulness of generated outputs can be affected by the quality of the prompts, feedback, and verification by humans. As such, AI literacy becomes a key component in the ability of product managers. Thus, AI literacy becomes a growing part of product-management competence.

B. Outcomes of AI-Augmented Product Management

1) Decision-Making Efficiency

Among the most immediate advantages of AI (augmented artificial intelligence) enhancement is the boost in decision-making effectiveness. AI can cut down the time needed for information processing, repetitive analysis, incorporation of customer feedback, forecasting, and documentation. Product managers can thus focus on strategic activities without spending a lot of time gathering and organizing information [26].

2) Decision Quality

AI may help to enhance the quality of the decision by feeding in vast amounts of evidence and uncovering patterns that might not be evident in manual analysis. Demand estimation, feature prioritization using recommendation systems, and integration of multiple customer/ market information sources are helpful uses of forecasting systems, recommendation systems, and analytical systems respectively. Improved decision quality, however, requires the quality of the underlying data, and the ability of the product managers to use the AI output suitably. So, AI does not necessarily guarantee improved decisions - it actually gives decision-support ability [27].

3) Innovation and Creativity

With generative AI, new possibilities are added for innovations with the ability to quickly create product concepts and different solutions, user scenarios, and communication approaches. This can help to create a wider solution space and help product teams test out ideas faster. Generative AI's potential for innovation is highest when its results inspire human exploration and are not taken as a given alternative to human creativity. Product managers need to continue to be the ones to find useful opportunities and link ideas created with real customer and market needs.

4) Performance impacts profitability

On the organizational level, AI augmentation can help achieve quicker product development cycles, enhanced customer responsiveness, better-informed resource allocation decisions, and sustained organizational learning. Monitoring them with the help of AI can offer immediate feedback on the performance of their products and predictive analysis can enable teams to foresee customer or market shifts. These capabilities can help you to establish a more adaptive product-management process that gets knowledge from one phase of the process to the next.

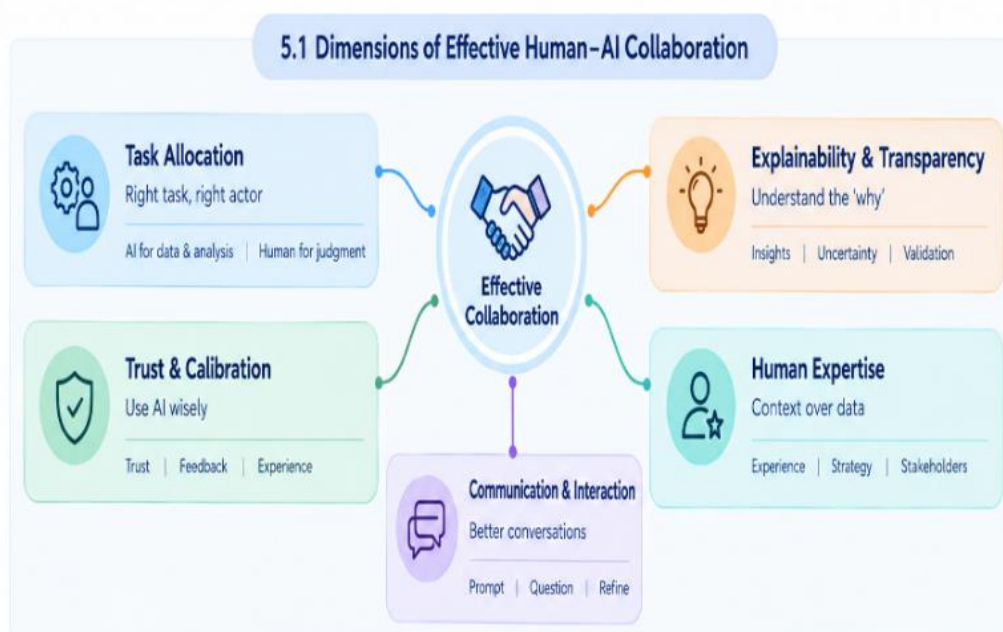


Fig. 5. Dimensions and Outcomes of Effective Human-AI Collaboration

Figure 5 summarizes this relationship by showing how task allocation, trust, explainability, human expertise, interaction, and accountability contribute to outcomes including decision quality, efficiency, innovation, product performance, and organizational learning.

C. Risks and Challenges

1) Algorithmic Bias

They can also replicate, or even magnify, any predisposition in the data used for customers, behavior, market, or past product information. Segmentation errors can lead to misrepresentation of groups of customers, and biased recommendation/prioritization systems can systematically benefit certain customers, features, or market segments. Assessing and monitoring bias is thus essential to guarantee that decisions made with AI do not lead to unfair or strategically biased results [28].

2) AI Hallucination and Reliability

Generative AI also poses the challenge of 'hallucination,' leading to the generation of content that seems possible but is incorrect, invented or unsupported. In product management, these outputs can influence market analysis, customer interpretation, requirements, product documentation or product recommendations. It is especially critical to obtain human verification if it is information that will affect consequential decisions.

3) Identify and explain over-reliance and automation bias.

As AI gets more capable, product managers may become more likely to take the advice of their AI without thoroughly evaluating it. This is especially problematic if AI-generated content is output with a high level of confidence but is actually uncertain. Clear responsibility and decision review processes, independent validation and clear processes for final decisions can help assure critical human judgment [27].

4) Accountability

An emerging governance challenge is who is accountable for the failure of a product decision when it is made with

the help of AI? Responsibility can be attributed to the product manager for having made the decision, the organization that put the system in place, the provider of the AI system, or several parties in total. To clarify the decision-making authority, escalation pathways, accountability for AI-driven results, and auditability, clear governance structures are necessary. With more autonomy for AI, these questions become more salient [28].

5) Private and Data Governance

Customer data, behavioral data, company-specific product data, and internal organizational knowledge are common sources of data for product-management AI. Such data, if used inappropriately, can pose privacy, confidentiality and security concerns. Organizations, then, need to have the right data governance, with respect to accessing the data, where it is stored, how it is used, how long it is kept confidential, and how sensitive data is protected.

6) Deskilling and Loss of Managerial Expertise

Overuse of AI can diminish over time the analytical independence, product intuition, critical thinking skills, and confidence in product decisions of product managers. Regularly relying on AI for analytical tasks could make managers less adept at handling complex scenarios on their own. It is therefore essential that domain and AI literacy continues to grow to ensure that AI complements and enhances managerial skills.

7) Organizational and Cultural Barriers (OCB)

Organizational readiness is also crucial in successful Human-AI collaboration. AI adoption can be hindered by employee resistance, lack of AI literacy, insufficient training, unclear AI governance, and concerns regarding evolving job roles. Organizations need to create proper training and communication, governance and experimentation environments. The introduction of AI is not just a technological endeavor, but also an organizational and cultural shift.

TABLE III. MAJOR CHALLENGES AND MITIGATION APPROACHES

Challenge	Potential Consequence	Mitigation
Algorithmic bias	Biased product decisions	Bias assessment and monitoring
Hallucination	Incorrect decisions	Human verification
Over-reliance	Reduced critical judgment	Decision review mechanisms
Opacity	Low confidence/transparency	Explainability
Privacy	Data misuse	Data governance
Deskilling	Reduced PM expertise	Continuous AI and domain training
Accountability	Unclear responsibility	Defined governance
Autonomous errors	Uncontrolled decisions	Human supervision

In summary, good Human–AI collaboration needs to combine the power of AI with the management of humans. AI augmentation will be most beneficial when systems grow intelligence without taking the place of human analysis, decision-making, and accountability. Then again, risks increase as AI systems assume more autonomy in making decisions that have more and more impact. The answer is not only more advanced AI systems, but also the right structures for collaboration, where, when and how to let the AI recommend, when to let the human decide and when to let the AI go it alone.

VI. Evolution of the Product Manager and the Emergence of Agentic AI

As AI becomes more powerful, its role in product management is set to undergo a paradigm shift, not just in the tools that are available to product managers, but in the very essence of what product management entails. The product manager might not directly perform the tasks of individual decision support but increasingly take on the role of coordinating and governing the process of using AI. This doesn't necessarily mean you are losing product managers. Rather, it proposes an evolution in which more human skills are introduced for setting goals,

measuring results, handling exceptions and guaranteeing that AI actions are aligned with customer, organizational and ethical needs[29].

A. From AI-Assisted Product Management to Human–AI Teaming

AI can be viewed as a tool that can grow a PM's maturity, ranging from Traditional PM to AI-Assisted PM to Human–AI Collaborator to AI Supervisor to Agent-Orchestrating PM. The traditional model involves product managers gathering information, weighing options and making decisions on their own. With an AI-assisted PM, AI primarily provides information, predictions, summaries, or recommendations. As systems get more interactive, the Human and AI collaborator shares and analyzes information with the AI while the latter suggests alternatives; the product manager evaluates and improves the suggested options.

As the product manager's role evolves, he or she becomes an AI supervisor, and AI systems take over a larger percentage of operational and analytical tasks supervised by humans. The new agent orchestrating PM is an evolution where AI specialists act as multiple agents,

carrying out complex and interdependent tasks, with the PM setting objectives, managing agents, checking

results, handling exceptions, and controlling the whole decision-making process.



Fig. 6. Evolution of Product Manager–AI Interaction

Figure 6. illustrates this maturity continuum. As AI capability and autonomy increase, the product manager's role progressively moves from directly executing analytical and decision activities toward evaluating, supervising, orchestrating, and governing AI-supported work.

B. Agentic AI in Product Management

1) AI Agents for Market Intelligence

Agentic AI might be able to track competitors, industry developments, consumer interactions, and market trends on a regular basis. Agentic AI could continuously observe competitors, industry changes, customer interactions, and market trends. Rather than having to begin product analysis, market intelligence agents could flag any changes that were relevant, then summaries the implications of these changes, and alert product teams of any major changes.

2) AI Agents for Product Analytics

Product-analytics agents would be able to keep an eye on product metrics, identify anomalies, investigate potential causes, explain the results and suggest interventions. It may change the way product analytics is viewed as a periodic reporting experience to something more continuous that is a decision maker's tool. However, human managers would still have to decide whether interventions that are recommended should be applied [30].

3) Development of a roadmap and planning support.

Agentic systems can also be used for roadmap management by comparing different scenarios, checking for dependencies, tracking progress of the development, and determining whether the development is deviating from its goals. Agents might suggest the modification of roads if market conditions, customer behavior or

development constraints change. But the key shifts in strategic priorities would still need to be assessed and authorized by human beings.

4) Multi-Agent Product Management

The next step is the development of multi-agent product-management systems, where specialized agents help each other do various tasks. For instance, dedicated agents might specialize in market research, understanding customer needs, product analysis, customer service, and marketing outreach. These would be able to share information and plan activities, forming an AI-driven product team. The product manager would progressively become an orchestrator with the role of setting goals, managing dedicated agents, reviewing their work, solving problems, and keeping the entire product line coherent.

C. Changing Product Manager Competencies

This change will demand product managers learn new skills in addition to their product-management skills. An understanding of system capabilities, limits, and outputs will be increasingly important for understanding the importance of AI literacy and data literacy. Product managers are also going to require greater capabilities in evaluating AI-generated outputs, managing agents, and human-AI interaction, as well as prompt or instruction development. With the rise of autonomy, being able to understand AI governance, risk management, privacy, transparency, and ethical decision making will become increasingly crucial.

The future product manager will not be characterized so much by his or her capability to do all the analytical and operational tasks himself or herself, but by his or her capability to frame problems, direct intelligent systems, evaluate evidence, make strategic judgments, coordinate AI agents, and take responsibility for outcomes of the product. The advent of agentic AI is not just about more automation, but a possibility for a reconfiguration of product-management tasks around human strategic leadership and AI-driven execution.

VII. Integrative Framework, Research Gaps

From discovery to strategy, development to launch, and post-launch efforts, AI is transforming product management. But AI's influence shouldn't be looked at in terms of any single technology or product management application. Lifecycle context, AI capability, human expertise, collaboration mechanisms, and governance are the essential elements that drive AI value, according to the central finding of this review. The integrative framework suggested in this section is built on this synthesis, which draws the connection between the AI capabilities and managerial expertise and product-management results through the prism of the Human–AI collaboration.

A. Proposed Integrative Framework for Human–AI Product Management

The proposed framework describes Human–AI product management as a multi-layered system in which product decisions are made when five main factors interact with each other: the product lifecycle, AI capabilities, human capabilities, coordination and collaboration mechanisms, and responsible governance. All these factors affect the use of AI for decision-making and the outcomes of such decisions in terms of products and organizations.

1) Product Lifecycle Layer

The first layer is the 8 phases of the product lifecycle: Discovery, Ideation, Strategy, Prioritization, Road mapping, Development, Launch, Post launch Optimization. There are different information needs, decision attributes, degree of uncertainty, and consequences of error in each stage. Therefore, the extent of AI use must differ from one stage of the lifecycle to another and cannot be a "one size fits all" approach.

2) AI Capability Layer

AI capability layer involves analysis, prediction, generation, recommendation, optimization and autonomous execution. These capabilities depict various degrees of AI's role. Written in a way that's easy for people to understand, analytical systems provide information, predictive systems predict how things will happen, generative systems create alternatives and content, recommendation systems facilitate choices, optimization systems find preferred configurations, and autonomous systems can increasingly carry out multi-step activities. Each capability will be suitable depending on the needs of the product-management decision.

3) Human Capability Layer

The human capability layer is defined by strategic judgment, contextual understanding, creativity, empathy, ethics and accountability. These skills help product managers to understand information in the context of the organization and customer, assess fuzzy options, identify stakeholders' concerns, and take responsibility for making consequential decisions. Human capabilities are thus not in opposition to, but supportive of, the capabilities of AI.

4) Collaboration Layer

The collaboration layer lies between AI and human capabilities, encompassing the use of AI assistance, human-in-the-loop decision-making, interactive collaboration, human-on-the-loop supervision, and agent supervision. The extent of the AI autonomy and the nature of the decision should match the collaboration mode. These tasks can be low-risk analytical, needing only small amounts of human intervention; they can be strategic or high-impact decisions that demand more human involvement.

5) Governance Layer

Responsible AI governance is embedded at each level of the framework. Trust, Explainability, Bias Management, Privacy, Accountability and Human Oversight are key governance dimensions. As AI systems become more self-directed, governance becomes even more critical since the potential for errors grows as the systems grow more capable and potentially more significant. Governance should thus be considered a life cycle need, not just something that occurs when implementing AI.

6) Outcome Layer

These layers interact with each other to yield results such as decision quality, efficiency, innovation, product performance, and organizational learning. The framework thus suggests the following central relationship

B. Human–AI Decision-Authority Model

Decision authority shouldn't be seen as a hard line between man and machine. Rather, it ought to be

adaptively set by the features of the task, the confidence of the AI, the ramifications of the decisions, uncertainty, and ethical sensitivity. The activities with lower risks and repetition could have more autonomy in the use of AI, while strategies and decisions with ethical implications will demand greater human control [31].

TABLE IV. HUMAN–AI DECISION-AUTHORITY MATRIX

Decision	AI Role	Human Role	Preferred Authority
Customer sentiment	Analyze	Interpret	Human-led
Feature ranking	Recommend	Validate	Shared
Market forecasting	Predict	Evaluate	Shared
Roadmap generation	Generate scenarios	Select	Human-led
Documentation	Generate	Review	AI-assisted
Product monitoring	Monitor	Intervene	AI-assisted
Routine optimization	Execute	Supervise	AI-led with oversight
Strategic direction	Support	Decide	Human-led

This matrix shows that collaboration should be "risk" based not "technology" based. The more powerful AI becomes, the more important it is to respect the need to transfer decision-making from AI to humans. The more capable AI becomes the more it is important to respect the need to transfer decision-making from AI to the humans. Rather, autonomy should be given as much as the system's reliability is sufficiently proven and the effect of any error is controlled accordingly.

C. Research Gaps and Future Directions

Despite rapid developments in AI-enabled product management, several important research gaps remain.

1) Limited End-to-End Lifecycle Research

Previous studies have tended to focus on specific tasks like customer analytics, recommendation, forecasting, and/or generative AI. Studies are still needed to explore Human–AI collaboration throughout the product lifecycle and how actions taken at one stage of the product lifecycle inform AI actions at another stage.

2) Empirical evidence that exists on Product Managers.

Further empirical studies are required to get a deeper understanding of the use of AI by product managers in organizational situations. Field/longitudinal studies need

to focus on the types of task delegation, type of assessment of recommendations, response to errors, and interactions with increasingly independent artificial intelligence systems among managers.

3) Optimal Human–AI Task Allocation

One of the big issues yet to be determined is what should be done humanely, with an AI or together with or under the supervision of an AI in a product-management process. More work is needed in the areas of task-allocation models for uncertainty, risk and reliability of AI systems, decision complexity and level of human expertise needed.

4) Trust and Over-Reliance

Trust calibration, the influence of explanations, reactions to failures of the AI, and automation bias are other elements of trust that could be explored further. For the creation of AI-driven decision support systems, it is crucial to grasp the appropriate acceptance and challenges of AI recommendations by product managers.

5) Agentic AI and Autonomous Product Management

As part of Agentic AI, there are several important research questions to consider. Future research should

explore the level of authority that should be given to an AI agent, how an AI agent is to be supervised, how multiple agents are to be coordinated and who is to be held responsible for the outcome of product decisions when autonomous agents are involved.

6) Measurement of Collaboration Quality

Standardization of the measures used to evaluate Human–AI collaboration is also needed throughout the research. These possible indicators range from decision quality and productivity, to innovation, trust, human satisfaction, transparency, to accountability. These would allow for comparisons between collaborations as they relate to various organizational contexts and collaboration designs.

7) Responsible and Ethical AI

Lastly, it would be interesting for future research to explore the aspects of bias, privacy, explain ability, governance and autonomous decision risk specifically in product management contexts. There is a need for lifecycle-specific governance frameworks to keep responsible AI principles embedded in development and use of products.

TABLE V. RESEARCH GAPS AND FUTURE RESEARCH DIRECTIONS

Research Gap	Current Issue	Future Research
Lifecycle integration	Fragmented studies	End-to-end lifecycle research
PM behavior	Limited empirical evidence	Field and longitudinal studies
Task allocation	Unclear responsibility boundaries	Human–AI allocation models
Trust	Risk of over/under-reliance	Trust-calibration studies
Agentic AI	Emerging research	Autonomous-agent experiments
Evaluation	Inconsistent measures	Standardized collaboration metrics
Governance	Fragmented approaches	Lifecycle governance frameworks

D. Theoretical and Practical Implications

1) Theoretical Implications

The review helps in understanding Human–AI teaming and AI-augmented decision making by introducing the idea of product management as a decision system involving human and AI systems, instead of a set of isolated AI applications. The proposed framework combines technological capabilities and human knowledge, cooperation, decision making and governance. It thus serves as a starting point for future research in the field of human-centered AI in knowledge intensive managerial tasks and will help to clarify the future possibilities of product-management tasks if AI becomes increasingly capable and independent.

2) Practical Implications for Product Managers

For practitioners, the results indicate that there is still a need to have human decision power for high impact, uncertain and ethically sensitive decisions, which is the role of product manager. The output of AI must be checked, not taken on face value and the use of AI to make decisions should be explained. Additionally, product managers need to become AI literate, data literate, and critical thinkers, and learn about the limitations of AI. The more powerful the agents, the more vital the managerial skill will be to supervise and orchestrate the agents.

3) Implications for Organizations

AI tools need to be complemented by the right governance, training, accountability and assessment systems, as well as human oversight. It's important to not see AI as just a technology that's being deployed. There should be clear decision rights within the organization that define when AI can recommend, act or make decisions on its own and when it requires human authorization. It is also important to create on-going monitoring to detect bias, reliability issues, privacy threats, and unanticipated independent behavior.

VIII. Conclusion

The use of AI is revolutionizing the product management landscape, impacting every aspect of the product lifecycle, from product information collection to product information analysis and from product information decision making to product information alternative assessment. This review demonstrates how the use of AI

is now moving beyond automation into decision augmentation, whereby analytical, predictive, generative and now more autonomous AI systems are augmenting human expertise. From initial customer discovery to ideation, product strategy and prioritization, road mapping, development, launch, and even post-launch optimization, AI has the potential to enhance these product-related tasks across all their stages. To reap these rewards, however, product managers and organizations must be able to set up such human–AI forms of collaboration.

The review reveals it is not simply about substituting one type of intelligence for another but complementary intelligence working together as a whole. AI tools can be especially effective for handling large data volumes, finding trends, predicting results, creating options, tracking results, and streamlining repetitive tasks. Product managers, on the other hand, bring in context, strategy, creativity, empathy, ethics, stakeholders' management and accountability. Thus, the best decision making occurs when AI helps to augment the information and choices available to managers, but the manager still has the right and final say on consequential decisions.

Additionally, the study notes that there are critical issues to consider when combining human and AI in collaboration. The value of AI support to decision-making can be decreased by algorithmic bias, hallucination, opacity, automation bias, over-reliance, concerns about privacy, deskilling, and unclear accountability. Therefore, the use of AI in product management must be judged on a holistic basis, not just for its efficiency or performance. Other key factors are trusting calibration, explainability, human oversight, responsible data practices, and decision authority that is clearly defined. This means that governance needs to be kept in view throughout the entire product life cycle and not considered as a technical issue.

This is more important in the age of agentic AI. As markets become more complex, AI agents can be increasingly involved in tracking the market, analyzing product metrics, creating roadmaps, managing work processes, and completing certain operational tasks without the need for human involvement. This will probably make the product manager's job more supervisory and orchestrating, instead of direct execution, more evaluation and governance. Instead of replacing the product manager, agentic AI can rather enhance the role of managerial skills that involve the

mastery of AI tools, managing agents, strategic decision-making, and responsible use of AI.

The overall conclusion of this review is that product management in the future must be seen as a system of decisions, in which humans govern and AI augments. AI can be applied to situations where it is easy to see its benefit in terms of scale, speed, prediction and automation, whereas humans need to play a role in situations where they need to make decisions that involve context, strategic thinking, ethical considerations and accountability. In the future, it is important to go beyond individual AI use cases and explore how people and AI work together throughout the entire lifecycle of a product (including empirical studies of product managers, task allocation models, trust calibration, agentic systems, collaboration quality measures and governance mechanisms). AI-driven research can be used to create more effective, transparent, and accountable product-management systems while still allowing for human oversight and responsibility, which can help organizations reap the benefits of AI.

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