The Evolution of Product Management Methods in the Era of Generative Artificial Intelligence

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Abstract

The article presents a comprehensive analysis of how generative technologies transform product management methods across different stages of the product lifecycle. The study is based on a systematization of modern approaches to applying generative models in ideation, user research, requirements formation, product design, go-to-market preparation, and post-release processes. The paper examines mechanisms that ensure the stability of decisions, including the use of synthetic data, scenario modeling, automation of analytical procedures, and agent-based coordination schemes. Particular attention is given to the asymmetry in method maturity, the impact of data quality on the reliability of conclusions, the requirements for interpretability, and the organizational constraints inherent in corporate environments. The analysis demonstrates that generative technologies reshape not individual stages but the structure of the entire product cycle, creating a continuous decision-making loop and redistributing responsibilities between analytical and engineering functions. The study concludes that the effectiveness of generative models is determined by the coherence of data, architecture, and development processes, which sets new requirements for integrating these technologies into complex products. The article will be useful for product management professionals, AI researchers, digital platform architects, and developers of corporate systems.

Keywords: generative technologies, product management, product lifecycle, synthetic data, agent-based models, corporate systems, interpretability.

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1. Introduction

Product management methods are rapidly changing under the influence of generative technologies. In corporate systems, where products include digital services, automotive solutions, and voice interfaces, value is determined by the ability of models to work with large and heterogeneous data. Generative AI are becoming the backbone of the entire product cycle, from idea origination to user experience analysis.

Management quality depends on the accuracy of pattern identification, forecasting, requirements formulation, and decision alignment. Synthetic data, scenario modeling, intelligent analysis, and the automatic creation of project materials play a substantial role. This is facilitated by modern learning methods, probabilistic inference, and adaptation mechanisms that ensure the operational stability of models.

In complex business products, the influence of generative methods manifests in accelerated design, reduced time-to-market, improved user scenarios, and increased analytics precision. In automotive systems, the reliability of forecasts and the ability to quickly adapt to new conditions are critical. In voice analytics, precise intent recognition is paramount. In corporate complexes, the automation of complex cognitive operations is essential.

The scientific novelty of the work lies in systematizing how generative technologies alter product management methods: which elements are strengthened, which processes are automated, and which limitations remain unresolved. Based on available research, an attempt is made to map the capabilities of generative models against all stages of product creation, distribute methods across stages, and identify key barriers affecting the stability and scaling of solutions.

The objective of the study is to determine how generative technologies transform product management methods at different stages of creation and to identify mechanisms that ensure the stability, speed, and accuracy of decisions made. To achieve this goal, the following tasks were set: to trace how the functional capabilities of modern generative models correlate with key development phases, and to establish the changes they introduce into the processes of ideation, requirements formulation, design, user experience analysis, and product market launch preparation.

The working hypothesis posits that the development of product management in the context of generative technologies is determined by the joint operation of three groups of mechanisms: extended user understanding systems, automated design cycles, and created behavioral models that ensure constant data interpretation. Their combination reduces uncertainty, accelerates decision preparation, lowers operational costs, and increases the reliability of product strategies.

The scope of the study is limited to products where generative technologies exert a direct influence on corporate software solutions, automotive systems, business platforms, and voice analytics services. Industry processes are considered only as a context defining the requirements for stability, response time, and the integration of models into existing technological platforms.

2. Materials and Methods

The methodological basis of the research is formed at the intersection of works on innovation management, generative technologies, and the evolution of product processes. This approach allows for the unification of several levels of analysis: data generation and interpretation mechanisms, changes in product management methods, and the influence of new technologies on development processes. Source selection was conducted based on criteria of scientific reliability, orientation toward the product cycle, and relevance (years 2023–2025). The analysis includes works published in peer-reviewed journals.

Corvello et al. [1] emphasize the significance of human-centric approaches during the transition to generative technologies. The work of Kumar et al. [2] shows that generative models can fulfill the role of project team members and influence early development stages. Leung et al. [3] propose a scheme for applying generative models in production processes, setting the basis for instrumental analysis. Mariani et al. [4] examine the development of generative technologies and their influence on innovation cycles, which defined the overview part of the methodology. Naheed et al. [5] analyze the role of generative algorithms in assessing user experience. Nikolić et al. [6] study the factors of generative technology's influence on the success of digital products, which is important for risk assessment. Ogundipe et al. [7] systematize the application of artificial intelligence at all stages of product creation, which sets the analysis structure. The research by Parikh [8] introduced ethical and organizational aspects, and Parikh [9] presented a model of agentic interaction. Practical scenarios for using generative technologies are described in the work of Venkat [10]. The final theoretical foundation is formed based on the analysis of Witkowski and Wodecki [11], where the role of artificial intelligence in key phases of new product development is demonstrated.

The methodological strategy is based on comparing the thematic directions described in the cited sources with the stages of the product cycle. Systematic analysis allowed for the identification of three key directions: the change in idea generation and analysis processes, the evolution of product design and validation mechanisms, and the restructuring of product management processes post-market launch. Collectively, these directions form the methodological basis for studying how generative technologies transform product management methods.

3. Results

The study revealed a steady transition from manual analytical procedures to multi-level processes based on language models. Kumar et al. [2] show that generative systems are capable of performing part of the analytical and design actions, forming a basis for the automated support of product processes. The transition to collaborative human-machine formats is also confirmed in the study by Parikh [9], which describes an agentic interaction model allowing generative tools to be viewed as participants in product processes. Similar logic is reinforced by practical observations in the study by Venkat [10], where generative mechanisms perform functions of analysis, requirements refinement, and material preparation at various development stages.

The expansion of analytical capabilities through synthetic data is emphasized in the study by Naheed et al. [5], which shows that artificially created user signals supplement the real sample and allow for the modeling of missing scenarios. The further significance of synthetic data is described in the study by Ogundipe et al. [7], which indicates that such data strengthen hypothesis testing and allow for the refinement of audience behavior models. Practical confirmation of this dynamic is presented in the study by Venkat [10], demonstrating the application of generative data for scenario formation and accelerated analysis.

The transformation of the product process extends beyond individual operations. Corvello et al. [1] show that generative approaches restructure the very architecture of innovation activity, increasing the speed and density of iterations. Further development of this direction is presented in the study by Mariani et al. [4], where generative methods are described as a catalyst for changes in innovation management, including idea generation and novelty assessment. The significance of comprehensive restructuring of product functions is confirmed by the structural analysis in the study by Ogundipe et al. [7], where artificial intelligence is distributed across key phases of the development cycle. Table 1 examines the distribution of generative technology capabilities across key product management functions.

Table 1 – Generative AI Capabilities Across Product Management Functions (Compiled by the author based on sources: [1, 4, 5])

Product Management Function	Generative AI Capabilities
Ideation & Concept Creation	Generation of ideas, scenario modeling, novelty analysis
User Research & CX Analysis	Synthetic user signals, reconstruction of behavioral patterns
Requirements Development and prioritization	Structured requirement generation, option formulation, and prioritization
Product Design Support	Multi-option conceptual design proposals
Decision Support	Agent-based reasoning chains
Go-to-Market Preparation	Automated creation of product materials and coming up with an initial GTM plan

The comparison of data presented in Table 1 shows that generative technologies are not an additional tool, but a holistic layer of intellectual support distributed across key product management functions. During early market exploration, generative methods enhance the detection of salient customer trends by substituting fragmented manual analysis with iterative procedures grounded in hypothesis formulation and empirical verification. In operational phases, they restructure work with requirements, ensuring rapid transitions between need formulation, implementation variants, and the assessment of design decision consequences. In later stages, up to product launch preparation, generative models perform a significant portion of routine and labor-intensive tasks related to material preparation, data systematization, and scenario refinement.

A comparison of functions shows that generative technologies influence different cycle stages unevenly. The deepest changes occur where work with abstractions, a multitude of variants, and high iteration rates is required. This result allows for the conclusion that the traditional linear structure of product management is losing rigidity, giving way to a continuous process in which data and decisions are updated synchronously.

Furthermore, the distribution of generative system capabilities across functions indicates a significant shift in the role of product teams. The human remains the bearer of strategic thinking and interpretation, while the majority of variable, analytical, and preparatory tasks are transferred to generative mechanisms. This means that the development of product management methods in the near term will depend not on the expansion of individual tools but on the degree of integration of generative technologies into the decision-making sequence. Based on the analysis, it is established that a new model of working with the product is being formed: continuous, iterative, data-rich, and relying on the joint action of humans and generative systems.

The comparison of artificial intelligence methods with new product development phases shows a pronounced shift of mature practices toward early stages. Kumar et al. [2] established that generative models ensure maximum efficiency gains precisely where a rapid transition from idea to primary requirement formalization is required. This is confirmed by the results of Leung et al. [3], which show that conceptual development benefits from the use of multi-model generation schemes allowing for the formation and comparison of solution variants prior to engineering detailing.

An additional contribution to the structure of early phases is provided by the use of synthetic data. Naheed et al. [5] show that user behavior modeling allows for scaling audience research without increasing time costs. The practical orientation of this approach is emphasized in the work of Venkat [10], where generative methods are applied to systematize materials and select directions for further design. The comprehensive review by Witkowski & Wodecki [11] demonstrates that late phases of the cycle—testing, market launch, and maintenance—possess a lower density of AI application methodologies, forming a structural gap in technology maturity.

The generalization of sources points to a consistent regularity: the less formalized the development phase, the higher the utility of generative methods. Ideation, conceptual development, and early audience research benefit from high variability, the possibility of rapid direction selection, and the ability to process incomplete data. Late stages are characterized by dependence on operational regulations and data stability, which restricts the application of generative tools to auxiliary functions. Table 2 examines the distribution of artificial intelligence methods across new product development phases.

Table 2 – Distribution of AI/GenAI Methods Across NPD Phases (Compiled by the author based on sources: [7, 11])

NPD Phase	AI/GenAI Methods Identified
Ideation	Idea generation, scenario modeling, and early requirement shaping
Concept Development	Multi-model conceptual design, rapid variant creation
User Research	Synthetic user data, behavioral reconstruction
Early Design & Specification	Structured requirements, design alternatives
Testing & Validation	Automated preparation of materials, assisted analysis
Go-to-Market & Post-Launch	Content generation, support for communication workflows

Sequential comparison of methods by phase allows for the conclusion of a systemic unevenness in the evolution of product practices. Generative models strengthen those parts of New Product Development (NPD) where uncertainty is a natural working condition, and prove less adapted to phases requiring stability and operational predictability. This creates a methodological divergence. Tools for early stages are becoming increasingly mature, while practices for late phases retain a fragmentary character.

Thus, the distribution of AI methods across NPD phases demonstrates an asymmetry reflecting the current state of theory and practice: generative tools are forming a new norm in ideation and conceptual design, whereas testing, market launch, and post-release processes require further development of adapted approaches.

4. Discussion

The results of comparing artificial intelligence methods with new product development phases show that the evolution of practices proceeds unevenly and forms structural fragmentation. Witkowski & Wodecki [11] emphasize that AI usage intensifies only at those stages where high solution variability and data uncertainty are permissible. This means that method maturity is not distributed evenly across the NPD cycle but is concentrated in the phases of ideation, design, and early analysis. The interpretation of this data allows for the conclusion that fragmentation is systemic in nature. It arises not from a lack of tools, but from differences in requirements for the reliability and controllability of decisions at later stages.

Data quality acts as a significant limiter. Nikolić and Bjelica [6] show that the success of an AI application depends on the stability of input information, and deviations create risks of unpredictable conclusions and redistribute responsibility among development participants. This indicates that even with advanced algorithms, AI implementation is complicated by the fact that product teams do not possess unified data validation standards. Such a situation reduces the probability of using AI in tasks related to testing, stability assessment, or market launch preparation, where an error leads to strategic losses. No less substantial is the deficit of transparency and ethical certainty. Parikh [8] established that the lack of explainability in AI decisions forms uncertainty in the distribution of responsibility and limits system scaling. If the interpretation of AI conclusions is difficult, teams prefer to keep methods within the bounds of auxiliary tasks and avoid including them in key decisions affecting safety, regulatory compliance, or market obligations. This creates a situation where AI potential is used only partially, and the most critical stages remain dependent on traditional manual practices.

Generalized analysis shows that the fragmentation of AI applications is not a temporary phenomenon, but a manifestation of systemic immaturity in the field. The aggregate of limitations regarding data quality, the necessity for interpretability, and high requirements for decision predictability at late stages explains why method maturity is skewed toward early phases. This gap is confirmed by all key sources and reflects a fundamental mismatch between the capabilities of modern generative systems and the conditions under which late product decisions are made. Table 3 presents the main challenges and identified gaps confirmed by the literature analysis.

Table 3 – Challenges and Gaps in AI-Enabled Product Management (based on sources [6, 8, 11])

Challenge / Gap	Description
Fragmented Adoption	Uneven integration of AI across NPD phases
Data Quality Risks	Sensitivity to inconsistent and low-quality data
Transparency & Ethics Issues	Risks linked to unclear decision logic and responsibility allocation

The analysis of the presented challenges demonstrates that the key problem lies not in the absence of technologies, but in the absence of conditions allowing for the transfer of AI methods to late development stages. The presence of high requirements for transparency, regulatory compatibility, and data stability leads to AI potential being realized only in specific zones, forming a fragmented application structure. This indicates the necessity of developing unified standards for data and transparency that could mitigate the identified limitations and ensure the integrity of the product cycle.

The presence of a unified data stack becomes a critical factor because modern generative methods require a stable and continuous supply of information. Kumar et al. [2] show that AI is capable of performing the functions of a project team participant, but the effectiveness of such participation is determined by the completeness and structured nature of data. Comparing these conclusions with data from Leung et al. [3] shows that in production scenarios, structuring requirements are even higher. Any data distortions at early stages lead to skewed design decisions. Consequently, a unified data architecture must integrate sources and set formal processing rules.

An important direction is the synchronization of product functions within a unified development chain. Naheed et al. [5] established that generative methods strengthen the link between user experience and product parameters. However, in the absence of a common architecture, this link breaks, and AI is used only at isolated points. The analysis by Nikolić et al. [6] confirms this problem, showing that implementation fragmentation intensifies the imbalance between analytical and operational development contours.

Context related to the client's application domain is of particular importance. For automotive systems, the requirement for decision explainability is critical, driven by the influence of AI on safety and forecast stability. Data interpretation requires architectures that allow for tracking the internal logic of model output, which aligns with Parikh's [8] conclusions on the importance of ethical transparency. In the sphere of corporate software systems, integrating generative methods into continuous integration and delivery processes allows for increased analysis accuracy and automated artifact preparation, confirmed by observations in Ogundipe et al. [7] regarding the role of AI in holistic development cycles. In the field of voice analytics, data from Venkat [10] demonstrates that the use of voice models strengthens the depth of understanding regarding intents and preferences, but requires strict synchronization with user scenarios and general data channels.

An important direction is linked to the concept of "agentic AI." Parikh [9] shows that distributed agentic models are capable of coordinating action sequences and ensuring autonomous decision-making. Including such structures in the general architecture allows for a transition from fragmentary application to complex processes in which AI independently links tasks, parameters, and dependencies between development stages.

Thus, the prospects for product management evolution are connected not with increasing the number of applied algorithms, but with forming a coherent architecture integrating data, functions, and responsibility levels. The formation of a unified integrated framework allows for the elimination of identified gaps, the improvement of decision quality, and the transfer of generative methods to stages that previously remained inaccessible.

5. Conclusion

The presented analysis has shown that the transformation of product management methods under the conditions of using generative technologies is determined not by individual tools, but by the coherence of the entire environment in which they function. Generative models exert influence only when data, development processes, and decision-making mechanisms form a continuous contour supporting stability and result reproducibility. The effectiveness of such solutions is based on the ability of systems to work with heterogeneous information, support the necessary pace of iterations, and minimize uncertainty when moving from idea to product release.

It is established that generative technologies restructure individual development stages and the structure of the product cycle itself. They alter the distribution of responsibility, complicate data processing logic, and require stricter coordination between analytical, engineering, and operational functions. It becomes obvious that the traditional linear model of product management is giving way to a continuous process where the results of analysis, design, and testing are updated synchronously and rely on a unified layer of generative support.

Verification of the identified regularities allows for the assertion that the key factors in the successful application of generative technologies are the coherence of data architecture, process resilience to input signal variability, and the infrastructure's capacity to ensure the operation of complex models without loss of predictability. It is these parameters that determine the boundaries of how deeply generative methods can be embedded into the product cycle and set the directions requiring priority development.

The results obtained allow for the formation of a basis for further research aimed at creating integrated approaches to product management. Questions regarding the construction of unified data stacks, the development of architectures supporting autonomous decision-making, and the design of interpretability mechanisms ensuring trust in model conclusions are of particular interest.

Thus, the generative approach forms a new understanding of how products should be created and evolved. It acts not as an auxiliary tool but as a principle of organizing the entire development system, where data, processes, and computations are viewed as a unified whole. This approach opens opportunities for creating more resilient and adaptive product solutions capable of meeting the complicated requirements of the corporate and technological environment.

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