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Theoretical Foundations of Decision-Making for Implementing Artificial Intelligence Technologies in Software Products

Elena Levi

Director of Product at Payoneer, Giv'atayim, Israel

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Abstract— *The study examines theoretical foundations for managerial decision-making on the implementation of artificial intelligence technologies in software products under conditions of accelerated prototyping, AI-supported software engineering workflows, and data-driven product development. The objective is to construct a conceptual decision model that links decision theory, organizational readiness, AI governance, and modern software product management practices. Within the research, existing approaches to AI-based decision-making, organizational AI implementation, and AI-driven software engineering are systematized. The conditions for the reliable deployment of AI functionality into production-grade software are analyzed. Special attention is paid to data quality, digital maturity, and responsible AI governance as determinants of adoption decisions. The methodological base combines a targeted review of recent scientific literature, comparative analysis of conceptual frameworks, and synthesis of a multi-level decision model for product leaders. The conclusions outline the stages and criteria for decision-making on AI implementation in software products, and provide practical guidelines for product leaders and software engineering managers seeking to evaluate AI opportunities, structure experimentation, and align AI-enabled prototyping with long-term product strategy and trust.*

Keywords*— *artificial intelligence implementation, software products, decision-making, product management, data-driven decisions, digital maturity, responsible AI governance, AI prototyping, software engineering, organizational adoption.

I. INTRODUCTION

Artificial intelligence has moved from experimental pilots to routine components of commercial software products, including SaaS platforms, marketing technology systems, and data-intensive services. AI-supported prototyping and AI-enabled code generation shorten the path from idea to interface, but, by themselves, do not answer whether a given AI feature deserves investment, integration into the architecture, and long-term support from engineering teams. Product leaders face not only the question of technical feasibility but also the challenge of structuring decisions about when, where, and how AI should be embedded into software products without eroding trust, maintainability, or customer value.

Existing research on AI and decision-making concentrates on multi-criteria decision-making, data-driven optimization, and human–AI collaboration. Studies of AI implementation in organizations describe antecedents, barriers, and consequences at the levels of processes, infrastructure, and people, yet rarely delve into the concrete decision logic of product teams responsible for software features. At the same time, work on AI-driven software engineering highlights fast-growing possibilities for AI-assisted coding, testing, and maintenance, but usually focuses on engineering practices rather than strategic product choices.

The purpose of the article is to develop a theoretical model of decision-making for implementing AI technologies in software products that integrates decision theory, organizational research on AI implementation, responsible AI governance, and data-centric product management. Three research tasks are formulated:

1) To systematize theoretical approaches to AI-related decision-making at individual, team, and organizational levels relevant for software product development.

2) To identify determinants of organizational readiness for AI implementation in software products, including digital maturity, data quality, and governance structures, through synthesis of recent empirical and conceptual studies.

3) To construct an integrated decision model for product leaders that links AI prototyping, experimentation, risk assessment, and responsible deployment across the product lifecycle.

Scientific novelty lies in focusing theoretical analysis specifically on the decision process of product leaders responsible for AI features, integrating organizational AI implementation frameworks with AI-driven software engineering and responsible AI governance, and reinterpreting them as a coherent decision-support structure for managing AI transformations in software products.

Contribution

This study contributes to research on artificial intelligence and information systems in three ways. First, it systematizes theoretical perspectives on AI-related decision-making and explicitly adapts them to the context of software product implementation, an area underdeveloped in the existing literature. Second, it integrates organizational AI adoption frameworks, AI-driven software engineering research, and responsible AI governance into a unified, multi-level decision model for product leaders. Third, it reframes AI implementation decisions as an ongoing product lifecycle process rather than a one-time technological choice, highlighting the roles of data readiness, digital maturity, and governance in sustaining AI-enabled software products.

II. MATERIALS AND METHODS

The theoretical basis of the study comprises ten scientific sources published between 2021 and 2025, selected through targeted searches in major academic databases (Scopus, Web of Science, ScienceDirect, MDPI, and others), using combinations of keywords related to artificial intelligence, decision-making, software engineering, organizational adoption, and governance.

M. Alenezi and M. Akour [1] analyze AI-driven innovations across the software engineering lifecycle and describe how AI tools support code generation, debugging, testing, and maintenance, emphasizing their influence on productivity, code quality, and development speed in professional environments. A. Al-Surmi, M. Bashiri, and I. Koliousis [2] develop an AI-based decision-making framework that combines marketing and IT strategies, using artificial neural networks to explore optimal strategic configurations and their impact on operational performance. G. Amoako and co-authors [3] propose a conceptual framework where AI systems affect entrepreneurial decision quality through customer preferences, industry benchmarks, and employee involvement, treating AI as a mediator of better strategic choices in emerging markets.

K. Al-Bukhaiti and co-authors [4] present a comprehensive review of decision-making in the age of AI, covering theoretical decision frameworks, multi-criteria decision-making methods, and computational tools, and analysing human–AI collaboration in complex decisions. K. Kovič and co-authors [5] examine the adoption of AI software in European manufacturing companies and show that the level of Industry 4.0 readiness and digital infrastructure strongly influences AI implementation. At the same time, basic firm characteristics play a minor role. M.C.M. Lee and colleagues [6] conduct a systematic literature review of AI implementation in organizations, identify themes across organizational, technological, information systems, and people-related dimensions, and propose a conceptual framework of AI implementation antecedents, challenges, and outcomes.

O. Neumann and co-authors [7] investigate AI adoption in public organizations using comparative case studies, highlighting governance, capabilities, and public value orientation as determinants of implementation decisions. An OECD report [8] characterizes AI adoption in firms across OECD and partner countries, documenting cross-country differences in the share of enterprises using AI and linking adoption to firm size, sector, and digital capabilities. E. Papagiannidis, P. Mikale, and K. Conboy [9] conduct a scoping review of responsible AI and propose a framework for responsible AI governance structured around structural, relational, and procedural practices across the AI lifecycle. B. Sattari and co-authors [10] design a theoretical framework for data-driven AI decision-making to enhance asset integrity management in the oil and gas sector, combining expert knowledge and AI/ML techniques to identify critical determinants in safety-critical infrastructures.

These materials collectively provide theoretical and empirical insights into AI-supported decision-making, AI adoption in organizations, software engineering practices, governance requirements, and sector-specific risk management, which are reinterpreted in the article from the viewpoint of product leaders making implementation decisions for AI features in software products.

The research methodology relies on a narrative and comparative review of the selected sources, structured thematic coding of decision-related concepts, and conceptual modelling. A comparative analysis is applied to identify convergences and differences among organizational AI implementation frameworks, AI-driven software engineering practices, and responsible AI governance models. The findings are synthesized into a multi-level decision model using methods of conceptual abstraction, typologization of decision criteria, and analytic generalization. The analysis focuses on extracting decision constructs relevant to product management in software companies, including evaluating AI opportunities, assessing readiness conditions, considering risk and governance considerations, and balancing accelerated prototyping with long-term product sustainability.

III. RESULTS

The theoretical analysis indicates that decision-making regarding AI implementation in software products follows a multi-level structure, combining individual, team, organizational, and ecosystem dimensions. The general decision-making frameworks summarized by K. Al-Bukhaiti and co-authors [4] indicate that contemporary decision theory is shifting from purely rational–calculative models toward integrative approaches, where multi-criteria optimization, bounded rationality, and human–AI collaboration coexist. In the context of product management, this means that choices about AI features cannot be reduced to a single metric. Product leaders simultaneously weigh customer value, data availability, technical feasibility, organizational capabilities, regulatory exposure, and long-term maintainability, while interacting with AI tools that both inform and constrain their judgments.

G. Amoako and co-authors [3] emphasize that AI-enhanced decision-making in entrepreneurial settings depends on how AI systems interact with customer preference signals, industry benchmarks, and employee involvement. Translated into software product practice, this suggests that AI functionalities in products should not be evaluated solely by internal efficiency or novelty, but by their capacity to surface reliable customer insights, position the product against industry standards and competitors, and mobilize cross-functional teams around shared evidence. When product leaders interpret model outputs alongside behavioral data and user research, AI becomes not a replacement for product sense but an amplifier of structured learning about markets and customers.

The organizational literature on AI implementation offers a structured framework for assessing readiness and constraints. The systematic review by M.C.M. Lee and colleagues [6] identifies organizational, technological, information systems, and people-related dimensions that shape AI implementation, including strategic alignment, governance structures, IT architecture, data infrastructure, skills, and change management mechanisms. In parallel, K. Kovič and co-authors [5] empirically show that the decisive factor for AI software adoption in manufacturing is not company size or position in the supply chain, but Industry 4.0

readiness and the presence of integrated digital infrastructures. For product leaders in software companies, these findings signal that decisions on AI features have to be embedded in a broader assessment of organizational digital maturity: whether data pipelines are trustworthy, whether deployment and monitoring processes can accommodate AI models, and whether the team has the competencies to operate and refine AI-enabled functionality over time.

Evidence from OECD enterprise surveys, synthesized in the 2025 report [8], provides an empirical backdrop for these theoretical considerations. The data show that, in 2023, the share of enterprises using at least one AI technology varies significantly across European countries, with Nordic economies achieving notably higher adoption rates than the EU average, while Southern European countries lag. This dispersion reflects differences in digital infrastructure, skills, and strategic focus, underscoring that AI implementation decisions depend on the surrounding ecosystem, including the availability of cloud services, regulatory expectations, and customer readiness. For software vendors operating in multiple markets, such heterogeneity directly influences which AI features are worth building, which must remain optional, and where the commercial return on AI investment is realistic.

Figure 1 illustrates that AI adoption across enterprises remains uneven despite overall growth. This heterogeneity reinforces the need for product-level decision frameworks that account for customer readiness and market context. AI features that deliver value in digitally mature environments may yield limited benefits or operational friction in less prepared segments, making selective, staged implementation strategies necessary.

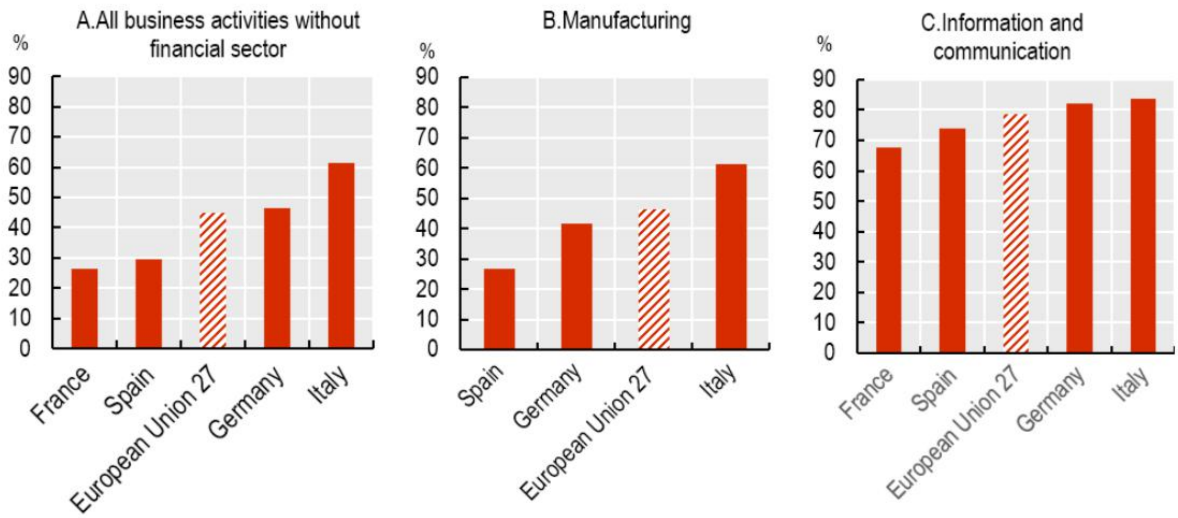

Fig.1. Share of enterprises that use at least one AI technology in selected European countries (2023), adapted from OECD [8].

AI adoption across enterprises is growing but remains uneven, underscoring the need for explicit decision frameworks at the product level. Where client organizations have low digital readiness, AI-heavy features may create more friction than value; in digitally mature client segments, the absence of AI capabilities can undermine competitiveness. Product leaders therefore face a portfolio of decisions: which AI opportunities to pursue for advanced customers, what minimum AI functionality is required to stay credible, and when to postpone AI implementation in favor of strengthening underlying data and workflow capabilities.

Studies focusing on AI-driven software engineering add another dimension to the field. M. Alenezi and M. Akour [1] demonstrate that AI tools already affect many phases of the software development lifecycle: code generation by large language models, intelligent debugging, automated test generation, refactoring recommendations, and predictive estimates of effort. These capabilities enable accelerated prototyping and AI-enabled code generation, where high-fidelity prototypes emerge from natural-language prompts in days rather than weeks. For decision-making, this changes the cost structure of experimentation: product managers can validate user flows, messaging, and initial interactions with minimal engineering effort. At the same time, the review highlights unresolved issues of trustworthiness, explainability, and integration across tools. From a theoretical standpoint, AI-assisted prototyping moves some decisions from the realm of abstract planning to empirically observable behavior much earlier. Still, it does not eliminate the need for rigorous evaluation before features are advanced into robust production services.

Operational research on AI-based decision-making provides concrete mechanisms for structuring complex choices. A. Al-Surmi, M. Bashiri, and I. Koliousis [2] propose a three-phase framework where AI models, built on artificial neural networks, explore performance implications of different combinations of marketing and IT strategies and support operations managers in selecting optimal strategies. Their work demonstrates how AI can be integrated into the decision-making process itself, not just as a feature in products. Applied to software product strategy, such models can support simulation of alternative AI feature roadmaps, pricing schemes, or levels of automation, helping product leaders understand performance trade-offs before committing engineering resources.

Sector-specific research in high-risk environments illustrates how theoretical AI decision frameworks operate under stringent reliability and safety constraints. B. Sattari and co-authors [10] design a data-driven framework for AI-supported decisions in asset integrity management, combining expert knowledge, machine learning, and keyword analysis to construct reaction networks and identify the most influential determinants of integrity in oil and gas systems. The central conclusion is the necessity of systematically linking AI outputs to domain knowledge, explicit risk tolerances, and inspection procedures. Translated to software products, particularly in regulated domains such as finance, healthcare, or marketing with strict compliance requirements, AI features must be justified not only by predictive accuracy but by their integration into controlled workflows, monitoring, and human oversight.

Responsible AI governance research adds a normative layer to decision-making. E. Papagiannidis, P. Mikalef, and K. Conboy [9] distinguish structural, relational, and procedural governance practices that operationalize responsible AI principles across the AI lifecycle. Structural practices concern roles, committees, and policies; relational practices govern stakeholder engagement and transparency; procedural practices regulate how models are designed, validated, deployed, and monitored. For product leaders, this framework implies that AI implementation decisions require explicit consideration of the following responsibility dimensions: fairness, transparency, robustness, accountability, and societal impact. AI features that accelerate user workflows but undermine transparency or create opaque dependencies on external models introduce hidden liabilities that product roadmaps must recognize.

Public-sector evidence from O. Neumann and co-authors [7] indicates that governance, capabilities, and public value orientation strongly influence AI adoption in public organizations. Their comparative case study reveals that even when technical AI solutions are available, decision-makers postpone or scale back implementation when interpretability is lacking, data quality is insufficient, or organizational mandates stress accountability and citizen trust. For software suppliers whose products serve both private and public clients, these findings underline that AI implementation decisions must be filtered through the lens of client governance expectations, not just technical feasibility or market hype.

Integrating the reviewed strands, a conceptual decision model for AI implementation in software products can be outlined. At the strategic level, product leaders formulate AI-related objectives, including differentiation, cost efficiency, personalization, and risk management. At the discovery level, AI-driven prototyping and AI-enabled code generation, as described by M. Alenezi and M. Akour [1], generate candidate solutions and interaction patterns with minimal investment. At the evaluation level, decision-makers apply multi-criteria frameworks inspired by K. Al-Bukhaiti and co-authors [4] and A. Al-Surmi et al. [2], balancing user value, technical feasibility, data readiness, compliance, and governance requirements. At the organizational level, the conditions identified by M.C.M. Lee et al. [6], K. Kovič et al. [5], and the OECD [8] define whether the firm and its customers are ready to sustain AI features over time. At the governance level, structural, relational, and procedural practices, as described by E. Papagiannidis and colleagues [9], determine the acceptable configurations of AI functionality in relation to trust and responsibility.

To make the synthesized decision logic operational and readable for product teams, the proposed model is presented schematically (Figure 2). The diagram separates decision layers across the product lifecycle and makes explicit the information flows linking strategic intent, AI-enabled discovery, evaluative gates, organizational readiness constraints, governance controls, and production feedback loops.

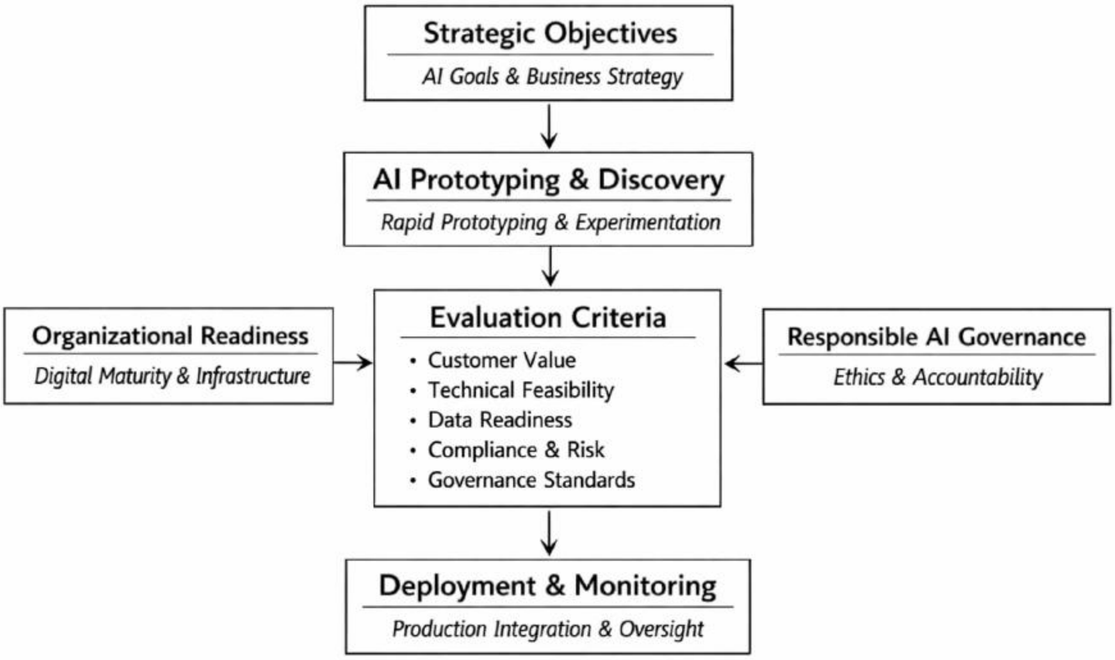

Fig.2. Multi-level decision model for implementing AI technologies in software products (conceptual synthesis based on [1; 2; 4–6; 8–10]).

Within this model, data quality and data-centric product management occupy a central position. Without reliable, well-understood data, AI features in software products degenerate into unstable prototypes that behave inconsistently across customers and environments. The frameworks of B. Sattari et al. [10] demonstrate that in safety-critical contexts, decisions rest on explicitly modeled relationships between variables and controlled data flows; an analogous discipline is required in business products whose decisions affect customers' finances, marketing outcomes, or reputations. For product leaders, investing in monitoring pipelines, data contracts, and feedback loops becomes a precondition for sustainable AI implementation, even if such work does not immediately yield visible interface changes.

In summary, the literature's theoretical foundations converge on a view of AI implementation decisions as structured, multi-level, and deeply intertwined with organizational maturity, governance, and data-centric practices. AI-generated prototypes accelerate discovery, but decisions on which prototypes evolve into trustworthy, scalable features depend on a layered evaluation of value, risk, and feasibility that extends beyond the surface allure of prototyping AI development.

IV. DISCUSSION

The synthesized decision model reveals several tensions that product leaders must address when considering the implementation of AI in software products. The first tension lies between the speed of prototyping and the depth of evaluation. AI-driven tools, as described by M. Alenezi and M. Akour [1], reduce the marginal cost of new ideas. Prompt-based prototypes produced via AI-enabled code generation support early demonstrations and stakeholder engagement. At the same time, organizational research indicates that successful AI implementation relies on digital maturity, governance, and data quality, which evolve slowly and necessitate deliberate investment. This asymmetry leads to an overproduction of prototypes relative to the organization's ability to industrialize them. A structured decision framework helps distinguish experiments intended to inform learning from those intended for production, preventing the product portfolio from becoming cluttered with fragile AI components.

A second tension concerns the locus of intelligence in decision-making. Multi-criteria and AI-based decision methods discussed by K. Al-Bukhaiti et al. [4] and A. Al-Surmi et al. [2] show that AI can support configuration of strategies and evaluation of options, yet do not eliminate the need for human interpretation, especially when criteria conflict or when data are incomplete. In product management practice, this means that algorithmic scoring of AI opportunities — based on estimated impact, confidence, effort, and risk — must remain subordinate to structured conversation within cross-functional teams. Human judgment connects AI-generated insights with qualitative knowledge of customers, markets, and organizational constraints.

To make the synthesis explicit, Table 1 brings together the main theoretical lenses used in the sources and their implications for product-level AI implementation decisions.

Table 1. Theoretical lenses relevant for AI implementation decisions in software products (based on [1–4; 6; 9])

Theoretical lens	Core focus for AI decisions	Implications for product leaders
Multi-criteria decision-making and optimization	Structuring trade-offs across multiple quantitative and qualitative criteria	Use scoring models and scenario analysis to compare AI feature options under uncertainty and competing goals.
Organizational implementation frameworks	Antecedents, challenges, and outcomes of AI deployment in organizations	Evaluate AI features against the firm's and its customers' digital maturity, skills, processes, and change readiness.
AI-driven software engineering	Automation of coding, testing, and maintenance through AI tools	Treat AI tools as accelerators of discovery and refactoring, not substitutes for architectural decisions.
Entrepreneurial decision-making	Influence of AI systems on opportunity evaluation and strategic choices	Align AI features with customer preferences, industry benchmarks, and internal stakeholder engagement.
Responsible AI governance	Principles and practices for ethical and accountable AI	Embed governance gates into product decision processes for AI features across the lifecycle.

Organizational implementation research offers insight into readiness and obstacles, but is largely agnostic to the specifics of software product lifecycles. AI-driven software engineering research excels at describing tooling and automation, but says little about product strategy or governance. Responsible AI frameworks define "how to behave" with AI, rather than "what to build" in specific products. Only by combining these lenses can product leaders produce decisions that are both theoretically grounded and practically actionable.

Empirical findings on AI adoption further refine the decision space. K. Kovič and co-authors [5] show low but growing AI software usage in manufacturing, with adoption strongly associated with Industry 4.0 readiness, while OECD data [8] reveal heterogeneous adoption rates across countries and sectors. For software vendors building AI-enabled products, these results suggest that a single, globally uniform AI roadmap is rarely optimal. Instead, decision-making must account for clusters of customers with different readiness profiles: some prioritize advanced AI capabilities, while others prefer stability and transparent workflows.

To clarify the connection between theoretical categories and concrete decision criteria in software product management, Table 2 summarizes key groups of criteria for AI implementation decisions and links them to evidence from the considered sources.

Table 2. Decision criteria for implementing AI functionalities in software products across the product lifecycle (based on [1–10])

Criterion group	**Typical evaluative questions for product decisions**	**Representative evidence**
Customer value and behavior	Does the AI feature solve a recurring customer problem, improve outcomes, or meaningfully reduce effort relative to alternatives?	Entrepreneurial decision models; AI-enabled operational performance.
Data readiness and quality	Are data sources complete, reliable, and stable over time? Are labeling, drift, and feedback loops manageable with existing resources?	Asset integrity frameworks; organizational implementation themes.
Digital and organizational maturity	Do engineering, DevOps, and MLOps practices support secure deployment, monitoring, and rollback of AI components?	Industry 4.0 readiness and AI adoption; implementation review; public sector adoption.
Governance and risk	Are fairness, transparency, privacy, and compliance requirements satisfied? Are accountability and escalation paths defined?	Responsible AI governance; public sector AI cases.
Experimentation and learning	Can the AI feature be evaluated through experiments, A/B tests, or quasi-experiments with clear success metrics and guardrails?	Decision-making frameworks; AI-based decision models; AI in software engineering.
Ecosystem and market conditions	Do target markets and client organizations have sufficient AI adoption, skills, and regulatory clarity to use and trust the feature?	OECD enterprise adoption data; sectoral readiness analyses.

Many AI ideas that appear attractive in demos fail when evaluated against data readiness, governance, or ecosystem conditions. Conversely, certain less spectacular AI functions — for example, invisible optimization of internal workflows or data quality — may score highly on sustainability and risk criteria, making them strong candidates for prioritization even if they are less visible in marketing materials.

From a product leadership perspective, the findings support several practical interpretations. First, AI-generated prototyping should be treated as an extension of product discovery rather than as evidence of implementation readiness. Prototypes help refine understanding of the problem, language, and user flows, but theoretical and empirical work on AI implementation cautions against equating prototype success with operational viability. Second, data-centric product management emerges as a structural prerequisite for AI strategies. Studies on asset integrity [10] and responsible governance [9] show that robust decisions depend on traceable, explainable data flows; in product terms, investment into telemetry, event models, and monitoring must precede large-scale AI rollouts. Third, decision-making on AI features benefits from explicit governance checkpoints, such as review boards or decision templates, that require product teams to articulate problem statements, expected impact, risk mitigation plans, and monitoring schemes before committing scarce engineering capacity.

Ultimately, the reviewed literature suggests that responsible AI and competitive advantage are not mutually exclusive. E. Papagiannidis and co-authors [9] argue that structural, relational, and procedural governance practices can be designed to support innovation rather than suppress it. When product leaders incorporate these practices into their decision frameworks, they establish a repeatable process for evaluating AI opportunities, including initial market discovery with AI prototypes, data readiness assessment, structured multi-criteria evaluation, governance review, and staged rollout with ongoing monitoring. For organizations experiencing transformation fatigue, where employees are subjected to continuous waves of "AI initiatives," a transparent, theory-informed decision-making process helps filter noise, reduce random experimentation, and focus attention on AI features that support coherent product strategies and trustworthy customer relationships.

Limitations and Directions for Future Research. This study is conceptual and does not empirically test the proposed decision model. While grounded in recent empirical and review-based research, the framework has not been validated through case studies, surveys, or longitudinal analyses of software product organizations. In addition, the focus on software and SaaS products may limit transferability to hardware-intensive or highly regulated embedded systems. Future research could empirically examine decision-making processes surrounding AI features, assess the relative weight of different decision criteria, and explore how governance and data maturity influence AI success across product portfolios.

V. CONCLUSION

This research reconstructs and integrates theoretical foundations for decision-making on the implementation of artificial intelligence technologies in software products.

Based on ten recent scientific sources, a multi-level decision model is synthesized that links individual and organizational decision frameworks, AI-driven software engineering tools, data-centric thinking, and responsible AI governance. The model views AI-generated prototyping as a powerful tool for discovery, but assigns significant weight to data readiness, digital maturity, governance practices, and ecosystem conditions when selecting AI features for industrialization.

The first research task is addressed through the systematization of decision-making frameworks, AI implementation studies, AI-based decision models, and responsible governance concepts, which collectively demonstrate that AI decisions cannot be reduced to isolated technical choices but instead depend on a structured evaluation of multiple criteria. The second task is to identify the determinants of organizational readiness, including Industry 4.0 maturity, architectural and data infrastructure, skills, and public value orientation, which condition the feasibility and sustainability of AI in software products. The third task leads to an integrated decision model for product leaders that filters AI ideas through customer value, data quality, governance, and ecosystem readiness, supported by explicit experimentation and learning mechanisms.

For product leaders and software engineering managers, the results suggest a practical trajectory: treat AI prototypes and AI-enabled code generation outputs as inputs into structured decision processes; build data and governance foundations ahead of large-scale AI integration; calibrate AI roadmaps to client readiness; and institutionalize multi-criteria and responsible AI perspectives in product decision forums. For researchers, the proposed model opens a path to empirical studies of decision processes surrounding AI features in real product organizations, including the measurement of how governance, data quality, and digital maturity influence the success of AI implementations within software portfolios.

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