ISTANBUL TECHNICAL UNIVERSITY ★ GRADUATE SCHOOL

UNINTENDED CONSEQUENCES OF GENERATIVE AI IN PRODUCT IDEATION: A PRODUCT MANAGEMENT PERSPECTIVE

M.Sc. THESIS

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İSTANBUL TEKNİK ÜNİVERSİTESİ ★ LİSANSÜSTÜ EĞİTİM ENSTİTÜSÜ

ÜRÜN FİKİR GELİŞTİRME SÜRECİNDE ÜRETKEN YAPAY ZEKÂNIN İSTENMEYEN SONUÇLARI: ÜRÜN YÖNETİMİ PERSPEKTİFİ

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Tuğçe Gültekin Atlı, an M.Sc. student of İTU Graduate School 507221040, successfully defended the thesis/dissertation entitled "UNINTENDED CONSEQUENCES OF GENERATIVE AI IN PRODUCT IDEATION: A PRODUCT MANAGEMENT PERSPECTIVE," which he/she prepared after fulfilling the requirements specified in the associated legislations, before the jury whose signatures are below.

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FOREWORD

In an era where Generative Artificial Intelligence is rapidly transforming business processes across industries, we find ourselves at a fascinating intersection of human creativity and computational capability. This thesis represents not merely an academic investigation but a timely exploration of how these powerful technologies are reshaping one of the most fundamental human activities in business: generating new ideas.

The journey toward completing this research has been both challenging and illuminating. What began as an interest in the efficiency gains promised by GenAI evolved into a deeper examination of the subtle ways these technologies influence our creative processes and decision-making patterns. Throughout countless interviews with product managers navigating this technological frontier, I witnessed firsthand the complex negotiation between embracing innovation and preserving the uniquely human elements of product ideation.

I am deeply grateful to the product managers who generously shared their experiences, challenges, and insights, allowing us to gain a deeper understanding of the real-world implications of this technological revolution. Their candid reflections on the benefits and unintended consequences of GenAI tools provide invaluable guidance for organizations seeking to implement these technologies thoughtfully.

Special thanks are due to my advisor, Prof. Dr. Deniz Tunçalp, whose guidance and expertise significantly contributed to shaping this research and whose encouragement sustained it through its most challenging phases. I am also indebted to the Department of Management Engineering at Istanbul Technical University for providing the supportive environment that made this work possible.

I want to express my heartfelt gratitude to my husband, Mehmet Anıl Atlı, for his unwavering support and encouragement throughout this academic journey.

I hope this thesis makes a meaningful contribution to understanding how GenAI can enhance, rather than diminish, human creativity in product development. As these technologies evolve, finding the optimal balance between computational efficiency and human ingenuity will remain crucial for organizations seeking sustainable innovation advantage.

Rather than offering definitive conclusions, this work aims to spark thoughtful conversation about how we might harness the remarkable capabilities of GenAI while remaining mindful of its limitations and potential consequences. The future of product ideation lies not in choosing between human or artificial intelligence but in discovering how these forces can most effectively complement one another.

Istanbul, June 2025 Tuğçe Gültekin Atlı

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ABBREVIATIONS

GenAI : Generative Artificial Intelligence
AI : Artificial Intelligence
NPD : New Product Development
IPA : Interpretative Phenomenological Analysis
HCD : Human-Centered Design
PRD : Product Requirement Document

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UNINTENDED CONSEQUENCES OF GENERATIVE AI IN PRODUCT IDEATION: A PRODUCT MANAGEMENT PERSPECTIVE

SUMMARY

This research examines the transformative impact of Generative Artificial Intelligence (GenAI) on product ideation processes within product management contexts. Through qualitative exploration involving semi-structured interviews with experienced product managers from both the B2B and B2C sectors, the study identifies critical unintended consequences that emerge when leveraging GenAI tools, such as ChatGPT, Midjourney, and Gemini, during ideation phases.

The methodology employed in this research consisted of in-depth, semi-structured interviews with product managers who have direct experience implementing GenAI within their ideation workflows. The interview protocol followed a three-step framework exploring a general understanding of GenAI, in-depth exploration of experiences with GenAI in new product ideation, and examination of unintended consequences and future perspectives. This approach enabled the collection of rich, qualitative data that captured both the immediate benefits and the subtle, long-term effects of AI adoption in creative processes.

The findings reveal a complex relationship between efficiency gains and creative limitations. While GenAI significantly enhances ideation productivity and streamlines documentation processes, it simultaneously introduces challenges, including creativity fixation, homogenization of innovation, decision-making biases, and ethical concerns related to intellectual property and data security. Product managers reported varying experiences based on their seniority, with experienced managers finding AI to be less creative but more practical for process refinement, while junior managers valued AI for suggesting concepts they might not have otherwise considered.

The research highlights how over-reliance on AI can gradually reshape cognitive patterns, potentially diminishing independent creative thinking. Additionally, the standardization of AI-generated outputs presents a risk of industry-wide homogenization of product ideas, thereby undermining competitive differentiation. The study also identifies verification challenges and trust issues that complicate the integration of AI-driven insights into strategic decision-making.

This thesis concludes by advocating for thoughtfully designed hybrid human-AI approaches that maintain human leadership in domains requiring creativity and judgment while leveraging AI for its efficiency and information synthesis strengths. It provides practical recommendations for product managers and organizations to establish effective governance frameworks and integration strategies that maximize the benefits of GenAI while mitigating its unintended consequences in product innovation.

Keywords: Generative Artificial Intelligence, Product Ideation, Creativity, Innovation, Unintended Consequences, Human-AI Collaboration, Decision-Making Bias, Ethics

ÜRÜN FİKİR GELİŞTİRME SÜRECİNDE ÜRETKEN YAPAY ZEKÂNIN İSTENMEYEN SONUÇLARI: ÜRÜN YÖNETİMİ PERSPEKTİFİ

ÖZET

Bu araştırma, Üretken Yapay Zeka'nın (ÜYZ) ürün fikir geliştirme süreçleri üzerindeki dönüştürücü etkisini ürün yönetimi bağlamında incelemektedir. ChatGPT'nin 2022 yılında piyasaya sürülmesinden bu yana, kuruluşlar bu teknolojileri yaratıcılığı artırmak, süreçleri hızlandırmak ve rekabet avantajı elde etmek için hızla benimsemektedir. Ancak bu hızlı adaptasyon sürecinde, bu teknolojilerin yaratıcı süreçler üzerindeki beklenmedik etkileri ve potansiyel olumsuz sonuçları göz ardı edilmiştir. Bu çalışma, B2B ve B2C domainlerinden deneyimli ürün yöneticileriyle yapılan yarı yapılandırılmış mülakatlar aracılığıyla yürütülen nitel araştırma kapsamında, ChatGPT, Midjourney ve Gemini gibi ÜYZ araçlarının fikir geliştirme aşamalarında kullanılması sonucunda ortaya çıkan kritik istenmeyen sonuçları belirlemektedir.

Araştırmada kullanılan metodoloji, ÜYZ'yi fikir geliştirme süreçlerine doğrudan entegre etmiş deneyimli ürün yöneticileriyle derinlemesine yarı yapılandırılmış mülakatlardan oluşmaktadır. Örneklem seçimi amaçlı örnekleme stratejisi kullanılarak gerçekleştirilmiş olup, 12 deneyimli ürün yöneticisi araştırmaya dahil edilmiştir. Bu katılımcılar hem B2B hem de B2C domainlerinden gelmektedir. Mülakat protokolü, ÜYZ'nin genel anlayışını, yeni ürün fikir geliştirmede ÜYZ ile deneyimlerin detaylı incelenmesini ve istenmeyen sonuçlar ile gelecek perspektiflerinin değerlendirilmesini içeren üç aşamalı bir çerçeveyi takip etmiştir. Bu metodolojik yaklaşım, yapay zeka adaptasyonunun yaratıcı süreçlerdeki hem doğrudan faydalarını hem de uzun vadedeki ince etkilerini yakalayan zengin nitel veri toplanmasına olanak sağlamıştır. Veri analizi sürecinde Gioia metodolojisi kullanılarak, katılımcıların ifadelerinden teorik boyutlara kadar sistematik bir kodlama süreci izlenmiştir.

Araştırmanın temel bulguları, verimlilik kazanımları ile yaratıcı kısıtlamalar arasında karmaşık ve çok boyutlu bir ilişki olduğunu ortaya koymaktadır. ÜYZ araçları, fikir üretim verimliliğini önemli ölçüde artırıp dokümantasyon süreçlerini kolaylaştırırken, aynı zamanda beklenmedik zorlukları da beraberinde getirmektedir. Katılımcıların tümü ChatGPT'yi günlük iş akışlarına entegre etmiş olup, bu araçları "asistan", "hızlandırıcı" veya "girdi makinesi" olarak konumlandırmaktadırlar. ÜYZ araçları özellikle dokümantasyon ve içerik biçimlendirme, fonksiyonlar arası iletişimi geliştirme, bilgi sentezi, fikir geliştirme desteği ve kullanıcıya yönelik içerik oluşturma konularında değerli bulunmuştur. Katılımcılardan bazıları, normalde günlerce süren görevleri çok daha kısa sürelerde tamamlayabildiklerini bildirmişlerdir.

Bununla birlikte, araştırma ÜYZ'nin radikal inovasyon ve derin analitik içgörüler sağlama konusunda önemli sınırlılıkları olduğunu ortaya koymuştur. Katılımcıların tümü, ÜYZ'nin mevcut kalıpları aşarak gerçekten yenilikçi fikirler üretmede başarısız olduğu konusunda hemfikirdir. Bu durum, yaratıcılık sabitlenmesi, inovasyonun standartlaşması, karar verme yanlılıkları ve fikri mülkiyet ile veri güvenliğiyle ilgili etik kaygılar gibi önemli istenmeyen sonuçlara yol açmaktadır.

Yaratıcılık sabitlenmesi, araştırmada tespit edilen en yaygın istenmeyen sonuç olarak karşımıza çıkmaktadır. Katılımcıların onda biri, düzenli ÜYZ kullanımının yaratıcılıklarını olumsuz etkilediği konusunda endişelerini dile getirmişlerdir. Bu durum, başlangıçta yaratıcı geliştirmeden nihai bağımlılığa doğru endişe verici bir ilerlemeyi göstermektedir. Katılımcılar, ÜYZ'nin kontrol davranışına yol açtığını ve bilişsel bağımsızlıkları üzerindeki etkilerini gözlemlemişlerdir.

İnovasyonun standartlaşması konusunda, tüm katılımcılar ÜYZ'nin gerçekten yenilikçi fikirler yerine standart, öngörülebilir çıktılar üretme eğiliminde olduğunu gözlemlemiştir. Katılımcılar, farklı ÜYZ araçları kullandığında "sonuçların çok benzer" olduğunu keşfetmiş, bu da standartlaşmanın farklı yapay zeka sistemlerine yayıldığını göstermektedir. Bu durum, yaygın ÜYZ benimsenmesi durumunda sektör genelinde ürün fikirlerinin homojenleşmesi riskini ortaya çıkarmaktadır. Katılımcılar ayrıca ÜYZ'nin mevcut pazar trendlerini yakalama ve alan spesifik anlayış geliştirme konusunda yetersiz kaldığını, çoğunlukla genel ve yüzeysel cevaplar verdiğini belirtmişlerdir.

Karar verme süreçlerinde ortaya çıkan yanlılıklar ve otomasyon bağımlılığı da önemli bir endişe kaynağıdır. Katılımcılar, üretici yapay zeka tarafından üretilen bilgileri doğrulamada önemli zorluklar yaşadıklarını, bazen doğrulanamayan bilgileri kaynak olarak kullanmak zorunda kaldıklarını belirtmişlerdir. Bu durum, karar verme zincirlerinde potansiyel yanlış bilgi yayılımına yol açabilmektedir. Özellikle uzmanlık alanları dışındaki konularda ÜYZ'ye bağımlı hale gelme riski bulunmaktadır.

Etik ve fikri mülkiyet konularında da önemli endişeler tespit edilmiştir. Katılımcılar organizasyonlarında üretici yapay zeka kullanımına yönelik resmi rehberlik bulunmadığını bildirmiş, bu da bireysel risk yönetimi stratejilerinin organik olarak gelişmesine yol açmıştır. Veri güvenliği, fikri mülkiyet sahipliği ve bilgi doğrulaması konularında belirsizlikler mevcuttur.

B2B ve B2C ürün yöneticileri arasında farklı deneyim kalıpları gözlemlenmiştir. B2B ürün yöneticileri, teknik dokümantasyon ve fonksiyonlar arası iletişim için üretici yapay zekayı daha kapsamlı kullanırken, B2C ürün yöneticileri kullanıcıya yönelik içerik oluşturma ve kullanıcı perspektiflerini anlama konusunda üretici yapay zekayı önemli bulmaktadırlar. Risk algıları da farklılık göstermekte; B2B yöneticileri veri güvenliği risklerine daha fazla odaklanırken, B2C yöneticileri tüketici trendlerini yakalama konusundaki sınırlılıklardan daha fazla endişe duymaktadırlar.

Katılımcılar, bu olumsuz etkileri azaltmak için sofistike adaptasyon stratejileri geliştirmişlerdir. Bunlar arasında üretici yapay zekaya danışmadan önce bağımsız düşünme, bağlama özgü güven kalıpları oluşturma, işbirlikçi filtreleme yaklaşımları geliştirme ve insan ile yapay zeka yetenekleri arasında stratejik görev dağılımı bulunmaktadır. Bu uygulamalar, üretici yapay zeka girdilerinin en çok değer kattığı alanları ve insan yargısının temel kaldığı alanları ayırt etme becerisi olan " Üretici yapay zeka okuryazarlığının" sezgisel gelişimini temsil etmektedir.

Araştırmanın sonuçları, üretken yapay zekanın ürün fikir geliştirme süreçlerinde hem önemli fırsatlar hem de ciddi riskler sunduğunu göstermektedir. Bu teknolojilerin etkin entegrasyonu, verimlilik ile yaratıcılık arasındaki dengeyi koruyacak stratejik bir yaklaşım gerektirmektedir. Çalışma bulgularına göre, en başarılı uygulamalar ÜYZ'yi rutin, yapılandırılmış görevlerde kullanırken, yaratıcılık ve muhakeme gerektiren alanlarda insan liderliğini koruyan hibrit modelleri benimseyen organizasyonlarda gözlemlenmiştir. Bu yaklaşım, yapay zekanın güçlü olduğu bilgi sentezi, dil işleme ve patern tanıma yeteneklerinden yararlanırken, insanların bağlamsal anlayış, stratejik vizyon ve çığır açan inovasyon kapasitelerini ön planda tutmaktadır.

Dikkatle tasarlanmış hibrit insan-yapay zeka yaklaşımları, organizasyonların rekabet avantajlarını kaybetmeden teknolojik gelişmelerden faydalanabilmeleri için kritik öneme sahiptir. Bu modellerde ÜYZ, geleneksel yaratıcılık metodlarını destekleyen bir araç olarak konumlandırılırken, nihai karar verme yetkisi ve yaratıcı kontrol insan ürün yöneticilerinde kalmalıdır. Araştırma, ürün yöneticilerinin ÜYZ'yi "asistan" veya "hızlandırıcı" olarak kullanırken, stratejik kararlar ve yaratıcı yönlendirme konularında insan önceliğini koruyan yaklaşımların daha başarılı olduğunu göstermektedir.

Organizasyonlar için kapsamlı ÜYZ yönetişim çerçeveleri oluşturulması kritik önem taşımaktadır. Bu çerçeveler, öncelikle veri güvenliği protokollerini içermelidir; hangi tür şirket bilgilerinin harici ÜYZ sistemleriyle paylaşılabileceğine dair net yönergeler, hassas bilgilerin korunması için güvenlik önlemleri ve veri sızıntısı risklerini minimize edecek kullanım sınırları belirlenmelidir. Fikri mülkiyet çerçeveleri açısından, ÜYZ destekli inovasyonlar için sahiplik ve atıf yaklaşımları netleştirilmeli, yasal doğrulama gereksinimleri tanımlanmalı ve potansiyel patent ihlali risklerine karşı koruma mekanizmaları geliştirilmelidir. Doğrulama standartları kapsamında ise, karar verme süreçlerinde kullanılan ÜYZ üretimi bilgiler için zorunlu doğrulama gereksinimleri, ek araştırma gerektiği durumların belirlenmesi ve faktüel doğruluk endişelerini ele alacak protokoller oluşturulmalıdır.

Bu çalışma, ürün yöneticilerine ve kuruluşlara ÜYZ'nin ürün inovasyonundaki faydalarını en üst düzeye çıkarırken istenmeyen sonuçlarını azaltacak çok boyutlu bir rehberlik sağlamaktadır. Pratik öneriler arasında, ÜYZ kullanımından önce bağımsız düşünmeyi teşvik eden sıralı fikir geliştirme süreçleri, yaratıcı çeşitliliği koruyacak değerlendirme kriterleri, farklı eğitim temelleri olan çeşitli ÜYZ araçlarının stratejik kullanımı ve ekip üyelerinin etkin insan-ÜYZ işbirliği becerileri geliştirebilmeleri için formal eğitim programları yer almaktadır. Ayrıca, organizasyonların düzenli ÜYZ etki değerlendirmeleri yapmaları, ürün farklılaşması üzerindeki etkilerini izlemeleri ve teknolojik gelişmelere paralel olarak yönetişim politikalarını güncellemeleri önerilmektedir. Bu kapsamlı yaklaşım, ÜYZ'nin sunduğu verimlilik artışlarından yararlanırken, yaratıcı farklılaşma ve inovasyon kapasitesinin korunmasını sağlayacak sürdürülebilir entegrasyon stratejilerinin geliştirilmesine olanak tanımaktadır.

Anahtar Kelimeler: Üretken Yapay Zeka, Ürün Fikir Geliştirme, Yaratıcılık, İnovasyon, İstenmeyen Sonuçlar, İnsan-Yapay Zeka İşbirliği, Karar Verme Yanlılığı, Etik

1. INTRODUCTION

The primary purpose of this thesis is to investigate the unintended consequences of Generative Artificial Intelligence (GenAI) in product ideation processes from a product management perspective. As organizations rapidly adopt GenAI tools to enhance ideation efficiency and creative outputs, there is a critical need to understand the full spectrum of effects these technologies have on innovation processes beyond the intended benefits.

This research aims to identify and analyze the unintended consequences that occur when product managers integrate GenAI tools, such as ChatGPT, Midjourney, and Gemini, into their ideation workflows, with a particular focus on potential creativity fixation, homogenization of innovation, decision-making biases, and ethical concerns. The study examines how product managers perceive and navigate these consequences in both B2B and B2C contexts, documenting their informal strategies for maintaining creative control while leveraging the capabilities of AI. Additionally, it examines the evolution of human-AI collaborative dynamics in ideation processes, investigating how dependency patterns may form and how cognitive approaches to creativity may shift over time with the continued use of AI.

Through this investigation, the thesis aims to develop a framework for understanding the complex relationship between efficiency gains and creative limitations when implementing GenAI in product development environments. The research provides actionable recommendations for product managers and organizations to establish effective governance structures and integration strategies that can maximize the benefits of GenAI while addressing potential unintended consequences.

By addressing these objectives, this thesis contributes to both the theoretical understanding of human-AI creativity and the practical implementation of GenAI tools in product management workflows. The findings aim to guide product managers toward a more thoughtful and strategic integration of these technologies, thereby enhancing, rather than potentially diminishing, human creative capabilities in the product ideation process.

1.1 Background and Significance of the Study

Artificial intelligence aims to replicate the capabilities of human minds, encompassing various psychological skills that facilitate goal attainment (Boden et al, 2018). Within this broader field, GenAI has emerged as a particularly transformative innovation in recent years, characterized by its ability to generate new content across multiple formats, including text, images, code, audio, and video (Faisal, 2024).

The rapid advancement of GenAI technologies is reshaping various industries and processes, with particularly notable impacts on creative and problem-solving domains. These technologies are influencing innovation processes, collaboration methodologies, and approaches to new product development by automating and augmenting tasks such as idea generation and decision-making. The International Monetary Fund's report, "GenAI: Artificial Intelligence and the Future of Work," suggests that these technologies have the potential to fundamentally transform the global economy, with advanced economies likely experiencing both the benefits and challenges sooner, due to their focus on cognitive-intensive employment structures.

Organizations are increasingly integrating GenAI into their operations to enhance creativity, streamline processes, and gain a competitive advantage. In the specific context of product development, GenAI is emerging as a significant force, particularly during the ideation phase, where it offers new approaches to generating and refining ideas. Gartner forecasts that by 2026, more than 80% of software vendors will have embedded GenAI capabilities in their products, highlighting the urgency for product managers to navigate this technological shift effectively.

1.2 Research Questions

This study examines the intersection of GenAI and product ideation processes through three interconnected research questions, providing a comprehensive framework for understanding both the transformative potential and complex implications of these technologies.

The first research question examines how generative AI impacts product ideation in new product development. This inquiry examines the impact of GenAI technologies on ideation practices, including their effects on efficiency, creativity, collaboration patterns, and ideation outcomes. It seeks to understand not only operational changes but also more fundamental transformations in how product ideas are conceived, developed, and evaluated when GenAI tools become integrated into established workflows.

Building on this foundation, the second research question focuses on identifying and analyzing the unintended consequences of using generative AI for ideation and innovation. This inquiry examines the effects that may emerge when product teams incorporate GenAI into their ideation processes, including potential creativity fixation, homogenization of innovation, decision-making biases, and ethical concerns related to intellectual property and data security. The aim is to document consequences that might counteract the intended benefits of GenAI adoption.

The third research question investigates how product managers perceive and navigate these unintended consequences in practice, exploring the strategies and adaptive approaches that product managers develop in response to challenges introduced by GenAI, examining how they balance leveraging AI's capabilities while maintaining creative control. It investigates their decision-making processes regarding when to rely on or override AI suggestions, as well as the informal governance mechanisms they establish to address potential risks. Additionally, it examines differences in perception and navigation strategies between experienced and junior product managers, as well as between B2B and B2C contexts.

Together, these research questions provide a comprehensive framework for understanding not only how GenAI may be changing product ideation processes but also the complex implications of these changes and the practical responses that product managers are developing to maximize potential benefits while addressing possible drawbacks.

The research is systematically segmented into three main stages, as outlined in Figure 1.1.

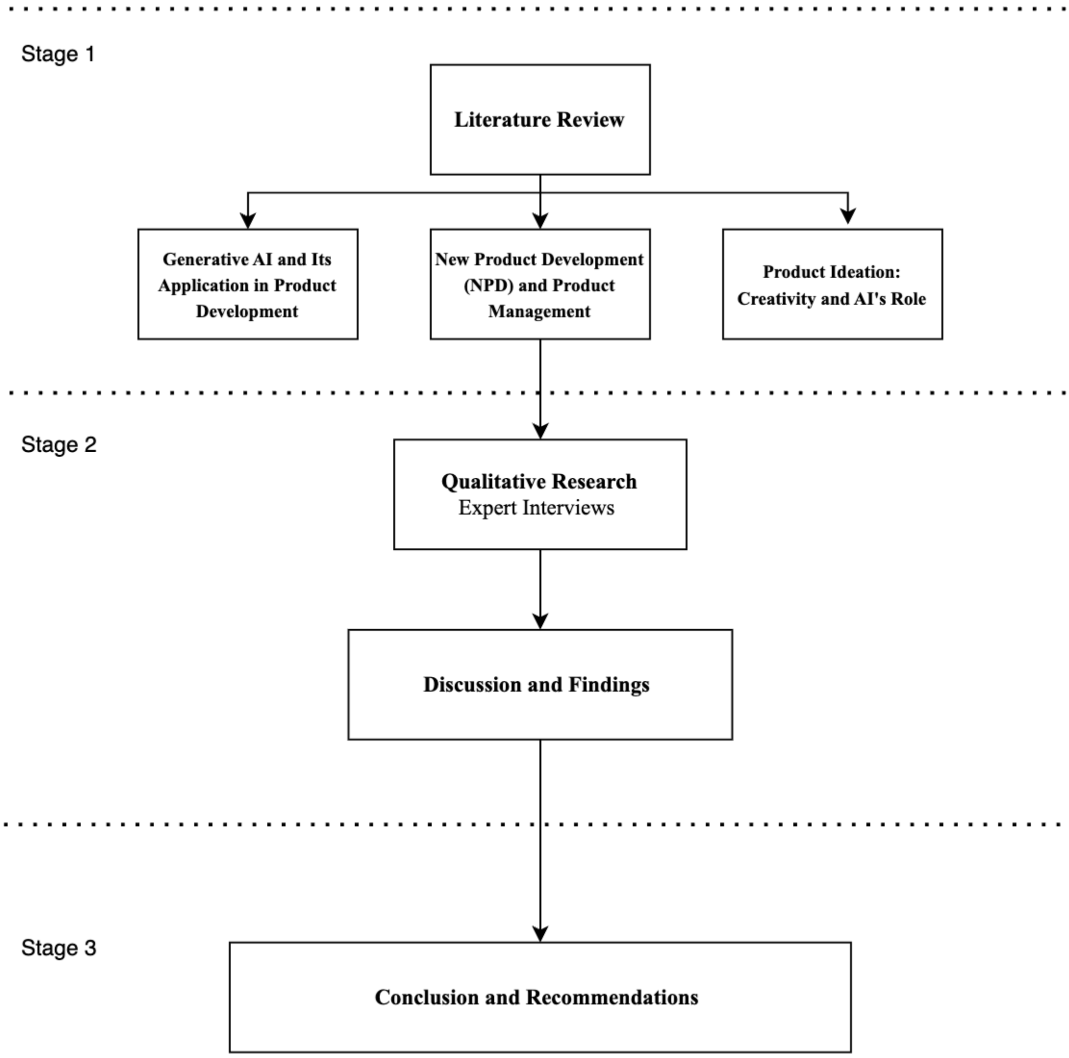

Figure 1.1: Thesis Structure.

The first stage establishes the academic foundation through an extensive literature review exploring generative artificial intelligence, new product development, and product ideation. This review examines the technological foundations and current applications of GenAI in product development, while identifying documented risks and challenges. It also clarifies the role of product management in new product development processes. It explores the complex relationship between human creativity and AI-assisted ideation.

The second stage focuses on qualitative research through semi-structured interviews with experienced product managers from both B2B and B2C sectors. This phase collects empirical data about real-world experiences with GenAI in product ideation processes, analyzing interview data to identify patterns, challenges, and adaptation strategies that practitioners have developed.

The final stage integrates theoretical insights with empirical findings to develop comprehensive conclusions. This synthesis advances conceptual frameworks for understanding human-AI collaboration in creative processes while providing actionable guidance for product managers and organizations seeking to integrate GenAI effectively while addressing potential unintended consequences.

This structured approach ensures a comprehensive examination of the topic while maintaining focus on the practical implications of GenAI integration in product ideation processes.

2. LITERATURE REVIEW

This section provides a comprehensive review of existing literature structured to address key aspects relevant to understanding the unintended consequences of Generative AI in product ideation. The review begins by exploring the foundational principles and characteristics of GenAI, tracing its evolution, and examining its current applications in product development contexts. While identifying the efficiency advantages GenAI offers in enhancing idea-generation processes, the review also critically examines the emerging challenges it presents to creativity and innovation practices.

The focus then shifts to the broader context of new product development (NPD) and product management, highlighting how ideation functions as a critical phase within the overall NPD process. This section evaluates traditional frameworks and contemporary approaches to product management, particularly how AI-driven strategies transform established practices and create new opportunities and challenges for product managers.

The final section investigates the complex relationship between GenAI and creativity in product ideation. Drawing on theoretical frameworks and empirical studies, this part analyzes how GenAI can simultaneously function as both a creative catalyst and a potential constraint. The review examines the nuanced interplay between human creativity and computational capabilities while also addressing the unintended consequences that may emerge from AI integration, including creativity fixation, decision-making biases, and the potential homogenization of innovation.

By systematically addressing these interconnected domains, this literature review establishes the theoretical foundation for investigating how product managers experience and navigate the unintended consequences of GenAI in ideation processes, laying essential groundwork for the following empirical investigation.

2.1 GenAI and Its Application in Product Development

GenAI has emerged as a transformative branch of AI that extends beyond traditional classification and analysis capabilities to create original content across multiple formats, including text, images, audio, and code. Powered by advanced machine learning architectures, particularly the large language models (LLMs), GenAI has garnered significant attention for its ability to simulate human-like creativity and generate contextually relevant outputs (Boden et al, 2018; Faisal, 2024).

Unlike traditional AI systems, which are primarily designed for information processing and pattern recognition, GenAI models produce novel and integrated outputs that have opened up new possibilities across diverse sectors. This capability has proven particularly valuable in creative domains such as product development, where ideation and innovation are central challenges. The distinguishing feature of GenAI systems lies in their ability to analyze existing information and synthesize it into new configurations that might not have been explicitly programmed or previously encountered (Jarrahi et al, 2023).

Integrating GenAI into product development processes significantly shifts how organizations approach innovation. Marcello et al. (2024) argue that GenAI will fundamentally change how NPD teams are constructed and operate, suggesting that team dynamics will evolve to accommodate the increasing inclusion of machine collaborators. They further propose that GenAI introduces a form of "positive randomness" that can stimulate creative thinking and lead to more diverse innovation teams, potentially reshaping the entire NPD process.

This section examines the definition and characteristics of GenAI, explores its specific applications in product development contexts, and investigates the technological foundations that have enabled its rapid advancement. While acknowledging the immense potential of these technologies to enhance creative processes, this review also considers the emerging risks and unintended consequences associated with their implementation in ideation workflows. By establishing this foundational understanding of GenAI, we create the necessary context for analyzing its complex implications for product management practices, which form the central focus of this research.

2.1.1 Definition and characteristics

AI has evolved into a captivating field that attracts widespread attention from researchers, industry experts, and the general public. Its growing prominence stems from its ability to produce increasingly realistic and creative outputs while becoming more accessible to users across diverse domains, including medicine, education, art, marketing, and software development. AI is an umbrella term encompassing various computational algorithms capable of performing tasks that traditionally require human intelligence, such as natural language understanding, pattern recognition, decision-making, and experiential learning (Leonardo et al, 2023).

Davenport et al. (2018) propose a practical framework for understanding AI through the lens of business capabilities rather than focusing solely on technological details. They identify three primary business functions that AI can support:

Process automation: The most common implementation involves automating digital and physical tasks, typically back-office administrative and financial activities, using robotic process automation technologies. These solutions advance beyond earlier business-process automation tools by enabling "robots" (server-based code) to interact with multiple IT systems in human-like ways.

Cognitive insight: Representing approximately 38% of AI implementations, these systems utilize algorithms to identify patterns within large datasets and interpret their significance. Operating as "analytics on steroids," these machine-learning applications extract meaningful insights from complex datasets.

Cognitive engagement: These implementations focus on engaging employees and customers through natural language processing chatbots, intelligent agents, and machine learning systems to facilitate human-computer interaction.

The emergence of GenAI marks a revolutionary advancement within the broader AI landscape. While traditional AI systems primarily focus on classification, prediction, and analysis of existing data, GenAI enables the creation of entirely new content that closely mimics human-created work (Mogbojuri, 2024). This trend represents a significant evolution from earlier AI systems, such as expert systems and knowledge bases, which operated primarily through rule-based decision-making frameworks.

From a terminological perspective, the descriptor "generative" refers to the ability "to produce or create something." Technically, all AI models generate outputs (whether numerical predictions or internal rules). GenAI refers explicitly to systems designed to create novel content with characteristics resembling human-created work. The distinctive feature of GenAI is its ability to generate outputs that extend beyond the explicit patterns in its training data, demonstrating a form of computational creativity (Boden, 2009).

Introducing accessible applications like ChatGPT, Gemini, and Midjourney represents a watershed moment in AI's evolution, making powerful Large Language Models (LLMs) and other generative systems available to general users. These tools have democratized access to sophisticated AI capabilities, enabling broad audiences to create human-like texts, realistic images, and other creative content without specialized technical knowledge. This accessibility has accelerated the adoption of GenAI within product development environments, where ideation and creative processes are essential activities (Piller et al, 2024).

In the specific context of product ideation, GenAI's characteristics are particularly relevant. These systems demonstrate capabilities for divergent thinking (generating multiple alternative solutions), contextual understanding (tailoring outputs to specific product domains), and creative recombination (synthesizing existing knowledge into novel configurations). However, they also demonstrate limitations in areas crucial to product innovation, including causal reasoning, deep domain expertise, and value alignment with organizational priorities (Elgammal et al, 2022).

As GenAI technologies evolve rapidly, understanding their fundamental characteristics and capabilities becomes crucial for product managers seeking to effectively integrate them into ideation workflows while being mindful of potential unintended consequences.

2.1.1.1 Understanding the GenAI technology

Generative AI encompasses algorithms designed to create new content across various media formats, including text, images, audio, and other data types, with outputs that closely resemble the patterns of the training data. These systems fundamentally differ from traditional AI by learning the underlying distribution of datasets and generating new data points that follow similar distributions. The field has evolved through several key architectural approaches, each with distinct capabilities and applications for product ideation (Mogbojuri, 2024).

Three primary model architectures dominate the GenAI landscape:

First, Generative Adversarial Networks (GANs) represent one of the most influential generative architectures, introduced by Goodfellow and colleagues in 2014. GANs operate through an adversarial process between two neural networks: a generator that creates synthetic data and a discriminator that evaluates the authenticity of the data. This competitive dynamic continues until the generator produces outputs that the discriminator cannot reliably distinguish from authentic examples. In product ideation contexts, GANs generate visual concepts and design variations that maintain fidelity to existing product aesthetics while introducing novel elements.

Second, Variational Autoencoders (VAEs) function by learning probability distributions of input data to generate new data points. The architecture consists of an encoder that maps the input to a latent space and a decoder that reconstructs data from this representation. VAEs optimize for reconstruction accuracy and conformity to the latent space distribution, typically following Gaussian patterns. Their ability to generate structured variations makes them valuable for exploring product design alternatives within constrained parameters.

Third, Autoregressive Models, including Large Language Models like GPT (Generative Pre-trained Transformer), generate content by sequentially predicting the next element based on previous elements. These models employ large-scale neural networks to model sequence distributions and generate coherent outputs by sampling from learned probabilities. This architecture powers most text-based GenAI tools in product ideation, enabling capabilities from requirement generation to concept elaboration (Leonardo et al, 2023).

The AI research community reserves the term "generative" specifically for complex models capable of creating high-quality, human-like material, distinguishing them from discriminative models (such as decision trees) that primarily predict probabilities of labels based on observations. This distinction highlights the fundamental difference in their approach: generative models learn comprehensive data distributions, whereas discriminative models focus on decision boundaries between categories (García-Peñalvo and Vázquez-Ingelmo, 2023).

Some examples of the so-called generative models include Generative Adversarial Networks (GANs) and Variational Autoencoders (VAE), among others (Figure 2.1). (García-Peñalvo and Vázquez-Ingelmo, 2023).

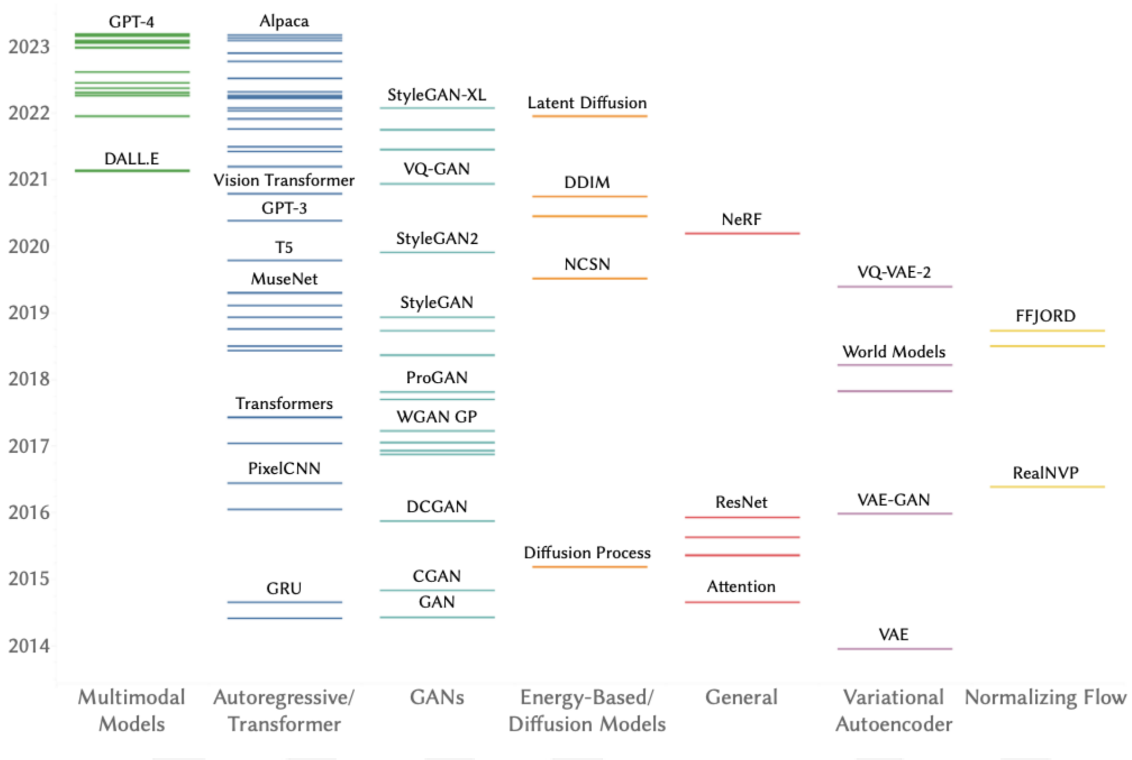

Figure 2.1: Timeline of generative models by type (García-Peñalvo and Vázquez-Ingelmo, 2023).

The training methodology for GenAI often employs semi-supervised learning, combining limited labeled data with extensive unlabeled data. This approach enables models to learn general patterns from vast datasets while refining specific capabilities through targeted examples. A distinctive feature of GenAI systems is their interaction paradigm, prompting users to engage with models using natural language to create desired outputs. Importantly, GenAI outputs are inherently probabilistic rather than deterministic, introducing variance that can be both beneficial for creativity and challenging for consistency in product development contexts (Figure 2.2) (Leonardo et al, 2023)

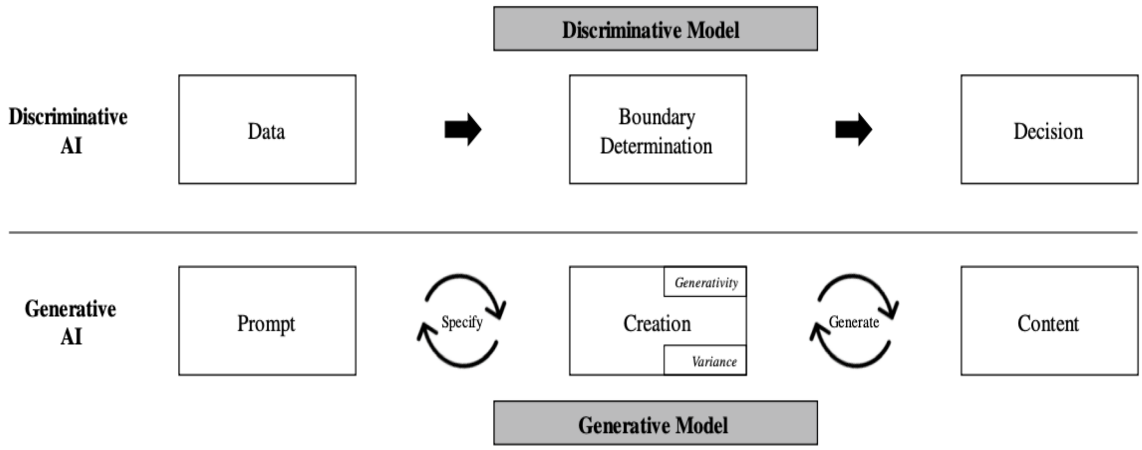

Figure 2.2: Procedural differences between generative and discriminative AI (Leonardo et al, 2023).

Examining the architectural framework of GenAI systems reveals three primary component layers (Figure 2.3). The model layer contains the core algorithmic capabilities. In contrast, the connection layer facilitates information exchange, and the application layer provides user interfaces and integration points.

This structure embeds GenAI within broader information systems, establishing boundaries for interaction with external entities, such as users and organizations (Leonardo et al, 2023).

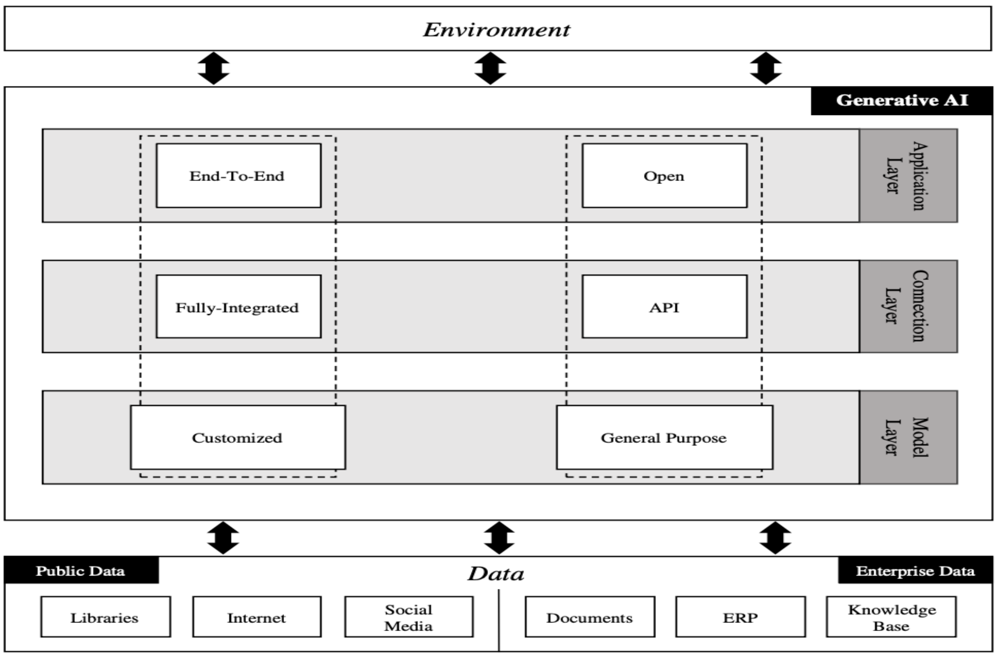

Figure 2.3: Conceptual Framework of Generative AI (Leonardo et al, 2023).

Recent advancements have produced two distinct categories of GenAI systems relevant to product ideation:

General models, such as ChatGPT, Gemini, and Llama, have been trained on diverse datasets spanning multiple domains. This phenomenon enables them to handle varied tasks by connecting information across knowledge areas. These models offer accessibility, speed, and broad knowledge that product managers can leverage for initial ideation and cross-domain inspiration. Their capacity for lateral thinking and creative connections makes them valuable for divergent thinking phases in ideation (Frank et al, 2024).

Expert models address the gap between sounding credible and delivering genuine domain expertise(Figure 2.4). These specialized systems integrate specific information into LLMs by fine-tuning existing models on domain-specific data or by prompt engineering. In product development contexts, expert models can provide more reliable guidance for industry-specific ideation challenges, particularly when regulatory, technical, or market-specific constraints must be considered (Frank et al, 2024).

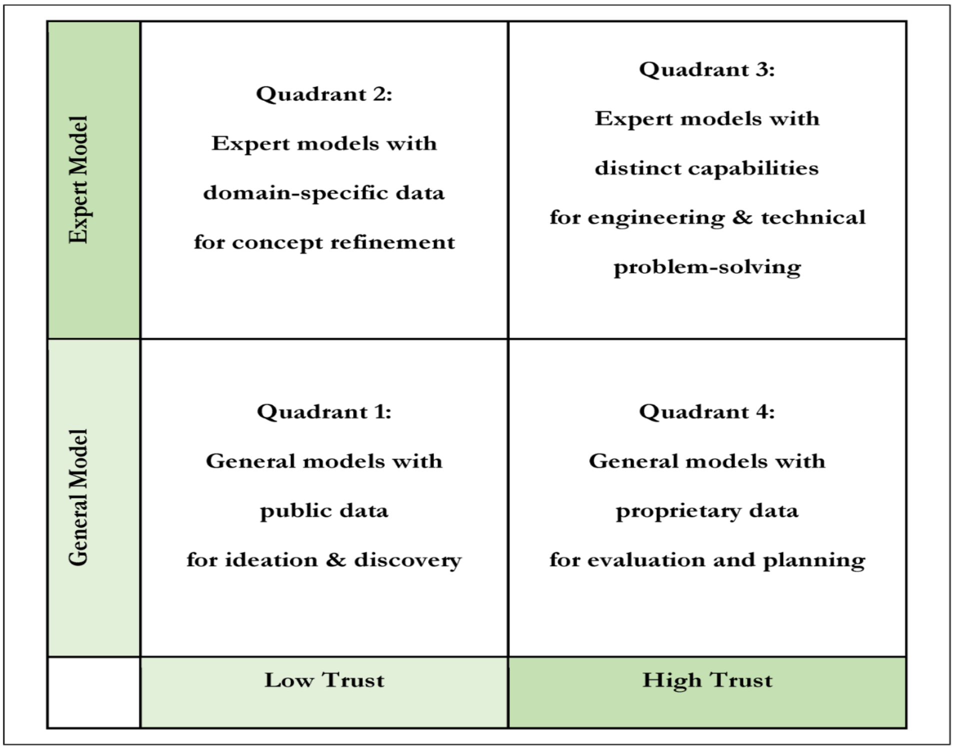

Figure 2.4: Matching GenAI applications to specific innovation tasks (Frank et al, 2024).

An emerging trend involves "AI agents," specialized models collaborating with other systems to create more connected and efficient AI ecosystems. This collaborative approach combines the strengths of individual expert models to provide comprehensive solutions, potentially enhancing the specificity and accuracy of GenAI contributions to complex product ideation processes (Xi et al, 2023; Frank et al, 2024).

For product managers seeking to implement GenAI in ideation processes, understanding these technological foundations provides essential context for matching appropriate GenAI applications to specific innovation tasks, balancing general creativity enhancement with domain-specific expertise requirements.

2.1.1.2 Usage of generative AI

The integration of artificial intelligence into business processes has accelerated across diverse industries, driven by promises of enhanced efficiency, precision, and improved decision-making capabilities (Gartner, 2023; McKinsey, 2022; IBM, 2022). This trend is particularly evident with GenAI, which has rapidly transformed from an experimental technology to a mainstream business tool. Organizations are increasingly adopting these technologies to process vast volumes of data, uncover hidden patterns, and empower more informed, data-driven decisions (Teng et al, 2022; Smit et al, 2022). While the potential benefits are significant, researchers caution that initial enthusiasm for novel applications often leads practitioners and academics to overlook potential adverse outcomes and unintended consequences (Mikalef et al, 2022; Al-Surmi et al, 2022).

The expanding body of literature exploring AI optimization, usage, adoption, and implementation (Benbya et al, 2020; Teubner et al, 2023) reflects the deep-seated integration of these technologies into organizational functions and business operations. This integration represents more than technological adoption; it signals a fundamental shift in how organizations approach creative and problem-solving processes across multiple domains.

The release of ChatGPT by OpenAI in November 2022 marked a significant milestone in the adoption of GenAI. This innovative large language model, capable of generating human-like content in response to varied prompts, attracted 100 million users within two months of its introduction (Paris, 2023). Lim et al. (2023) define GenAI as a technology that "(i) leverages deep learning models to (ii) generate human-like content (e.g., images, words) in response to (iii) complex and varied prompts." This technology has since revolutionized practices across multiple sectors, from artistic production (Zhou and Lee, 2024) to education and business operations.

ChatGPT's ability to understand and generate reliably concise responses in natural language (Mollick, 2022) has particularly disrupted the education and EdTech sectors. Applications range from developing course curricula to creating customized student tutorials, with major platforms like Duolingo and Khan Academy implementing GenAI tutors based on ChatGPT technology (Shah, 2023). The unpredictable nature and potential for unintended consequences of these technologies demand scrutiny across all implementation domains (Singh, 2023).

2.1.2 Applications in product ideation

In product development contexts, GenAI is extensively utilized across multiple stages of the ideation process, including brainstorming, benchmarking, concept development, and persona analysis. This integration represents a fundamental shift in how product managers and development teams conceptualize new offerings. As Gault (2018) notes, product ideation is a critical foundation for innovation, aligning with established categories, including product, process, organizational, and marketing innovation.

The application of GenAI in ideation processes spans both incremental and radical innovation approaches. In the innovation literature, radical innovations are defined as "fundamental changes that represent revolutionary changes in technology... clear departures from existing practice," while incremental innovations represent "minor improvements or simple adjustments in current technology" (Dewar and Dutton, 1986). According to Marcello et al. (2024), GenAI can support both innovation types, with particular value in domains where physical constraints are minimal, allowing for more expansive creative exploration. The technology's capability to introduce "positive randomness" can amplify human capacity to develop unconventional ideas during the NPD process, helping bridge the gap between deliberate and emergent innovation strategies.

This distinction between deliberate and emergent strategies in product development is particularly significant when considering the role of GenAI. While emergent strategies often arise through serendipitous discoveries by employees and managers, GenAI can systematically produce unexpected solutions through programmed elements of "positive randomness," potentially amplifying humans' capacity for unconventional thinking during the NPD process (Marcello et al, 2024). This capability may help organizations balance the tension between structured innovation approaches and more exploratory, emergent pathways.

A critical consideration in GenAI implementation is whether these systems function as co-creators collaborating with human teams or as potential replacements for human creative input. The research suggests that the most effective implementations position GenAI as an augmentation tool rather than a substitution technology. Marcello et al. (2024) observe that human-GenAI collaborations can significantly impact workflow structure, duration, and efficiency while enabling more real-time experimentation and validation. This collaborative approach enables innovation managers to rapidly iterate ideas and quickly process consumer preferences and needs through techniques such as digital prototyping.

In practical applications, GenAI enhances product ideation through several specific mechanisms:

Divergent thinking enhancement - Generating numerous alternative concepts quickly to expand the solution space (Muller and Bostrom, 2023). This capability addresses a standard limitation in human brainstorming, where cognitive biases and group dynamics can constrain idea generation. GenAI systems can produce hundreds of concept variations without fatigue or social inhibition, significantly expanding the ideation solution space.

Knowledge recombination - Creating novel connections between disparate domains to inspire innovative approaches (Verganti and Norman, 2022). By training on diverse datasets spanning multiple disciplines, GenAI can identify non-obvious relationships between concepts from different fields, potentially leading to breakthrough innovations through interdisciplinary inspiration.

Rapid prototyping facilitation - Accelerating the creation of conceptual prototypes to enable faster feedback cycles (Chen and Kim, 2024). GenAI can quickly generate visual representations, descriptive content, and interaction flows that enable stakeholder feedback at much earlier stages in the development process, reducing costly iterations later in the product lifecycle.

User persona development - Generating detailed user archetypes based on demographic and behavioral data to enhance empathetic design (Schuller et al, 2023). GenAI can synthesize complex user research into coherent, multidimensional personas that help product teams maintain a human-centered focus throughout the development process.

Market trend analysis - Processing vast amounts of market data to identify emerging patterns and opportunities that might not be apparent through conventional analysis (Hammond and Christensen, 2022). This capability helps product teams anticipate market shifts and align ideation efforts with evolving customer needs.

Constraint-based ideation - Generating solutions simultaneously satisfying multiple, sometimes contradictory, design constraints (Zhao and Bhattacharya, 2023). GenAI can explore viable solution spaces more systematically than unstructured human brainstorming by explicitly modeling design requirements and limitations.

These applications demonstrate how GenAI can potentially transform traditional ideation activities into more systematic, data-informed processes while still maintaining space for creative exploration. The technology's ability to rapidly generate and evaluate numerous alternatives offers product managers unprecedented abilities to explore concept variations and identify promising directions for further development.

2.1.3 Unintended consequences of generative AI

Despite these valuable applications, the emerging literature identifies several patterns concerning the unintended consequences of GenAI implementation. Issa et al. (2023) document three specific unintended consequences in organizational contexts: "impairment of digital agility, technostress, and process reengineering (redesign)." Their study of an EdTech startup demonstrates how AI adoption can create unexpected challenges that affect organizational performance and employee well-being.

Digital agility, an organization's ability to rapidly adapt to changing technological environments, may be compromised when teams rely on specific AI workflows. Technostress manifests as employees experiencing pressure to continuously adapt to new AI capabilities while questioning their value and role security. Process reengineering occurs as organizations restructure established workflows to accommodate AI integration, often creating unexpected inefficiencies during transition periods.

The "homogenization hypothesis" emerges as a particularly significant concern for product ideation. Anderson et al. (2023) found that "different users tended to produce less semantically distinct ideas with ChatGPT than with an alternative creativity support tool." While individual users generated more ideas with greater detail when using AI, they also reported feeling less responsible for the ideas generated. This argument suggests that while GenAI may increase individual productivity, it could potentially reduce the diversity of ideas across teams or organizations, a critical consideration for innovative product development.

The homogenization effect observed with GenAI in ideation processes appears to operate through several mechanisms documented in the literature:

Training data bias - Anderson et al. (2023) note that GenAI systems inevitably reflect patterns prevalent in their training data, potentially reinforcing dominant design paradigms rather than enabling truly disruptive thinking. Similarly, Bender et al. (2021) caution that large language models risk "stochastic parroting" of existing patterns rather than generating genuine innovations.

Prompt convergence - In their experimental study, Anderson et al. (2023) observed that "different users tended to produce less semantically distinct ideas with ChatGPT than with an alternative creativity support tool," suggesting that even with different users, AI systems tend to produce more homogenized outputs compared to traditional brainstorming methods.

Reduced ownership of creative outputs - Anderson et al. (2023) explicitly found that ChatGPT users "felt less responsible for the ideas they generated" compared to users of traditional creativity support tools. Hsu and Bechky (2023) further supported this psychological distancing effect, observing that human creators may become less personally invested in the outputs as creative agency is attributed to AI systems.

Statistical optimization bias - Elgammal et al. (2022) explain that the mathematical optimization processes underlying GenAI systems inherently favor statistically likely outputs over truly novel combinations, as these systems are fundamentally designed to minimize prediction error rather than maximize creative divergence.

These mechanisms collectively contribute to what Hsu and Bechky (2023) describe as "a homogenization of what is creatively produced as outputs," raising significant concerns for product differentiation and innovation distinctiveness in competitive markets.

Hsu and Bechky (2023) extend this concern to broader societal implications, noting that "generative AI improves efficiency and the average quality of a creative product; it also tends to reduce the advantages of expertise and induce a homogenization of what is creatively produced as outputs." This homogenization effect raises concerns about long-term impacts on creative professions and product differentiation in competitive markets. Their research suggests that as GenAI tools become more widespread, the distinctive advantages of human expertise may be diminished, particularly in domains where creative variation drives market value.

In the specific context of persona analysis during product ideation, Schuller et al. (2023) highlight that automated persona generation may lack the empathetic understanding present in manual creation. This reduction in psychological connection could lead to diminished empathy with AI-generated personas, undermining the human-centric nature of product development processes. Their research indicates that while AI-generated personas may be more comprehensive in representing demographic and behavioral variables, they often lack the emotional resonance and contextual nuance that emerge from human-created personas developed through direct user engagement.

The effective integration of GenAI in ideation requires thoughtful collaboration between human creativity and artificial capabilities. Piller et al. (2024) emphasize that generic GenAI models "are not explicitly trained for specific markets" and, therefore, despite producing fluent and seemingly credible responses, may not provide sufficiently trustworthy insights for advanced innovation stages requiring domain specificity and accuracy. Their research distinguishes between ideation tasks, where creative exploration is valuable (and AI "hallucinations" might contribute positively to divergent thinking), and evaluation tasks, where accuracy is essential (and such deviations could lead to costly errors).

Additional concerns include technical limitations such as "hallucinations" or fabricated facts and references (Ji et al, 2023). However, recent developments combining generative outputs with web search capabilities have reduced this tendency. Piller et al. (2024) suggest a structured approach to mitigate these risks, recommending that organizations structure their tasks based on the level of trust required when engaging GenAI to support development processes, determine when general AI models are sufficient versus when customized domain-specific models are necessary, and ensure users possess appropriate skills and capabilities to leverage different AI models effectively.

This framework acknowledges that different innovation tasks require varying specificity and accuracy, with early-stage ideation potentially benefiting from GenAI's creative variability. At the same time, later-stage decision-making demands more reliable, domain-specific insights.

Intellectual property considerations represent another emerging challenge. Marcello et al. (2024) suggest that the advancement of GenAI may render existing intellectual property protections obsolete, necessitating new conceptualizations of IP management in innovation contexts. The ambiguous ownership of AI-generated ideas raises complex questions about attribution, originality, and protection, calling for updated regulatory frameworks and closer coordination between GenAI providers and intellectual property authorities to establish clear guidelines for innovation in an era of machine-assisted creativity.

Data security and privacy concerns also emerge when organizations integrate sensitive business information into GenAI workflows. The potential for proprietary data to influence model training or inadvertently leak through responses presents significant risks that must be managed through appropriate governance structures (Vokinger and Gasser, 2023).

As GenAI adoption in product ideation continues to accelerate, understanding its transformative potential and unintended consequences becomes increasingly important for product managers seeking to integrate these technologies effectively while mitigating associated risks. The research suggests that while GenAI offers unprecedented capabilities to enhance ideation processes, its implementation requires thoughtful governance, precise task alignment, and careful consideration of potential negative impacts on creative diversity, empathetic understanding, and intellectual property frameworks.

2.2 New Product Development (NPD) and Product Management

New product development and management are critical in today's competitive business landscape. Organizations across industries rely on systematic approaches to innovation and product lifecycle management to maintain market relevance and drive growth. This section explores the foundational concepts of product management, examining its evolution from traditional definitions to contemporary practices influenced by technological advancements, including artificial intelligence.

The literature reveals that product management encompasses tactical implementation and strategic direction-setting, with varying definitions across different organizational contexts. Despite this variation, its importance cannot be overstated; successful product management directly correlates with organizational performance, competitive advantage, and long-term sustainability. As noted by several scholars (Berek, 1998; Gorchels, 2000; Johnson, 1999), considerable ambiguity exists regarding the roles and responsibilities of product managers, despite the importance of product management.

Most firms constantly strive to develop innovations, aiming to create new products and improve existing ones. Although challenging and risky, new product development has enormous potential benefits, including gaining market share, improving existing product sales, and retaining customers (Goldsmith, 2012; Jusufi et al, 2020). From a strategic perspective, new products that are well-aligned with customer voices, feature perceived technical superiority, and are launched ahead of the competition provide real competitive advantages (Cooper and Kleinschmidt, 1987; Crawford, 1994).

As technology continues to evolve, particularly with the emergence of generative artificial intelligence, product management is undergoing significant transformation, creating opportunities and challenges for practitioners in approaching the ideation, development, and management of new products.

2.2.1 Defining product management

Product management has been extensively studied in the literature from various perspectives. A fundamental distinction exists in conceptualizing it: the practical implementation of managing products versus a broader strategic framework that guides the entire process. This distinction helps us understand how product management functions tactically and strategically within organizations.

Despite varying conceptualizations, product management remains the predominant organizational mechanism for managing products compared to alternatives such as functional structures or key account management (Howley, 1988; Skenazy, 1987; Workman, Homburg, and Jensen, 2003).

The role definition of a product manager varies considerably across companies. In some organizations, particularly those focused on software development, the term "software product manager" is used, emphasizing the management of products within software development processes. In other companies, the product manager focuses more on market positioning and product growth strategies.

As Springer and Miler (2022) note, the primary focus of software product management is ensuring economic success by extending the product lifecycle while minimizing expenditures to maximize profits. Software product managers occupy a crucial position in development organizations, responsible for strategy, business cases, product roadmaps, high-level requirements, deployment (release management), and retirement planning. These responsibilities highlight the critical intersection between strategic decision-making and day-to-day product management operations.

According to Kittlaus and Fricker (2017), product management responsibilities are crucial in software companies, as they support decision-making processes and valuable product development. This argument broadens product management's scope to include both profitability and market leadership as central goals, ensuring that product managers play a pivotal role in sustaining product success.

Software product management encompasses defining, introducing, developing, growing, maintaining, and withdrawing software products from the market. It connects closely with other software engineering areas, including strategy development, requirements engineering, project management, agile development, product marketing, and business analysis (International Institute of Business Analysis, 2015; Project Management Institute, 2017). This interconnectedness demonstrates that product management is not a singular activity but a complex and collaborative effort involving multiple organizational functions.

As product management processes evolve, frameworks like Scrum provide valuable support in managing software products. These frameworks integrate well with other organizational functions, enabling more agile and responsive product development approaches. According to Schwaber and Sutherland (2017), Scrum supports product management as a framework by facilitating continuous improvement of the product, team, and working environment. The Scrum Guide introduces the role of the Product Owner, who is responsible for business goals and value. However, it does not precisely specify how this role should be performed effectively.

The literature emphasizes that successful management of products throughout their lifecycle is essential for driving growth and profitability. Product management oversees the introduction of new products and the effective management of existing ones, making it a key responsibility for companies seeking a competitive advantage.

As noted by several scholars (Berek, 1998; Gorchels, 2000; Johnson, 1999; Katsanis, Laurin, and Pitta, 1996; Low and Fullerton, 1994; Lysonski, 1985; Sands, 1979), despite product management's importance, considerable ambiguity exists regarding product managers' roles and responsibilities and the factors driving effective product management performance.

The product management literature contains numerous studies examining factors determining the success or failure of new products, including product superiority, early product definition, market research quality, top-management support, and execution quality (Cooper, 1975, 1979, 1990; Cooper and Kleinschmidt, 1987; Cummings, Jackson, and Ostrom, 1989; Lilien and Yoon, 1989; Montoya-Weiss and Calantone, 1994).

2.2.1.1 Product management framework

The Product Management Lifecycle framework represents the comprehensive journey of a product from initial conception through eventual retirement (Geracie and Eppinger, 2013). According to Springer and Miller, this lifecycle encompasses several key product stages: development and acquisition, market introduction, growth phase, and withdrawal. The framework further delineates activities occurring when products are already marketed, including commercialization and manufacturing operations, while acknowledging that software product management challenges may arise throughout the entire lifecycle.

This product management process is structured into seven phases: Conceive, Plan, Develop, Qualify, Launch, Deliver, and Retire. Critical decision points: Between these phases lie milestones that require significant business decisions. At each decision point, management can choose to (1) proceed to the next stage, (2) cancel the project, (3) redirect efforts based on strategic changes or gaps, or (4) defer the decision temporarily.

The Pragmatic Framework (formerly known as the Pragmatic Marketing Framework) offers an alternative perspective, outlining seven key areas and 37 related activities in technology product marketing and management (Pragmatic Institute, 2020). While not explicitly using the term "product management," this framework covers numerous aspects of software product management, including market analysis, product strategy development, business modeling, sales planning, and support functions. However, software product management extends beyond this framework due to the software's distinctive nature, incorporating user experience research, adaptation to rapidly changing technologies, iterative agile-inspired development methodologies, and continuous experimentation. This broader scope positions the Pragmatic Framework as particularly valuable for adjacent roles, such as executive leadership, sales, marketing, and support, rather than specifically for software product managers.

Research by Springer and Miler (2018) indicates that a software product manager's role and responsibilities significantly depend on company size. Key differences manifest in role staffing, scope of responsibility, tools and techniques employed, and engagement models with target customers. Larger organizations typically distribute some product management activities across multiple supporting roles. At the same time, smaller companies require product managers to handle numerous activities independently. Despite these variations, the archetype of the software product manager emphasizes common role elements, regardless of organizational size.

Interestingly, studies have revealed that only a minority of product managers are responsible for end-to-end product success, with most focusing primarily on core product management activities rather than supporting functions. While companies commonly evaluate product management performance through annual targets, such as sales growth or market expansion, only approximately one-third of them delegate financial KPIs directly to product managers (Ebert and Brinkkemper, 2014), suggesting potential disconnects between responsibility and accountability in many product management structures.

2.2.2 Stages of the new product development process

New product development (NPD) represents a strategic imperative for organizations across diverse sectors. While inherently challenging and risk-laden, NPD offers substantial potential benefits, including expanded market share, enhanced sales of existing products, customer retention, and increased funding opportunities. The critical importance of effective NPD is highlighted by research indicating that approximately half of all corporate sales derive from products commercialized within the preceding three years, underscoring that successful product development cannot be left to chance (Goldsmith, 2012; Jusufi et al, 2020).

From a strategic perspective, products that effectively respond to customer needs, demonstrate technical superiority, remain within budget constraints, and launch ahead of competitors provide significant competitive advantages (Calantone and Cooper, 1979; Cooper and Kleinschmidt, 1987; Crawford, 1994; Hultink et al, 1997). The focus of product development has undergone considerable evolution. While previous decades emphasized tangible product creation, contemporary approaches prioritize developing ideas, plans, strategies, and solutions. Additionally, the growing emphasis on sustainability has shifted the paradigm from products being merely "new and improved" to becoming "new to improve" society (Joore, 2010).

Research demonstrates the central importance of new products to organizational success. A 1986 analysis estimated that 40% of U.S. manufacturers' sales came from products introduced within the previous five years. Senior executives, by an eight-to-one majority, anticipated increasing dependence on new products, with a PwC survey confirming that most companies heavily rely on NPD for future growth and profitability (Cooper and Kleinschmidt, 2011).

Three decades of research reveal that the NPD process follows a series of development stages, interspersed with evaluative phases. These evaluative stages function as "gates" (Cooper, 1990) or "convergent points" (Hart and Baker, 1994) that help managers navigate potential go/no-go errors. During evaluations, management employs various techniques to develop commercially and technically viable product designs. However, despite normative guidelines supporting the development of new product configurations, the criteria for evaluating performance at different stages often remain imprecise (Hart et al, 2003). A significant, yet overlooked, issue concerns whether identical criteria sets apply at every decision point or if individual criterion weightings vary across decision stages (Ronkainen, 1985).

The NPD process typically encompasses six key stages:

Idea Generation: The systematic pursuit of new product ideas through both internal sources (R&D, employee contributions) and external channels (distributors, suppliers, competitors, and especially customers). Companies typically generate hundreds or thousands of ideas to identify a few promising concepts (Claessens, 2015; Quain, 2019).

Idea Screening: Filtering ideas to select those aligned with organizational objectives while eliminating weaker concepts early. This stage begins to narrow options, as development costs increase significantly in subsequent phases (Claessens, 2015).

Concept Development: Converting promising ideas into intellectual property while minimizing material and manufacturing costs. This phase incorporates technical, labor, development, tooling, and capital equipment considerations (Annacchino, 2007; Quain, 2019). Companies develop alternative product concepts to assess customer appeal and select optimal approaches.

Concept Testing: Transforming attractive ideas into detailed product concepts in meaningful consumer terms. Companies distinguish between product ideas (possible products), product concepts (detailed versions in consumer terms), and product images (consumer perceptions). Testing typically employs focus groups from target audiences to evaluate factors like usability, traction, and purchase intent (Claessens, 2015; Quain, 2019).

Marketing Strategy Development: Testing products and proposed marketing programs in realistic market settings before full-scale investment, allowing for the evaluation of targeting, positioning, advertising, distribution, and packaging strategies. The extent of test marketing varies based on investment requirements, risk levels, and the certainty of product and marketing program effectiveness (Claessens, 2015).

Commercialization: Introducing the product to the market after its development is complete. A product launch has a significant impact on long-term success, with continued marketing efforts post-launch being crucial; a common mistake is discontinuing marketing efforts after the initial introduction. Significant resources may be directed toward advertising, sales promotion, and marketing during the first year, with timing and placement considerations being crucial (Claessens, 2015; Quain, 2019).

Despite careful development, market failure rates for new products remain strikingly high. Research by Clancy et al. (2006) indicates that failure rates for new consumer services, business products, and business services reach approximately 90%, with no more than 10% achieving success even after three years (Hasani and Beqaj, 2021), underscoring that successful NPD requires more than simply applying development steps, it demands comprehensive planning, practical methodologies, and strategic execution across all stages. The NPD process can determine the difference between product success and failure in competitive markets.

2.2.3 Evolution of product management with GenAI

The product management discipline has evolved significantly with the emergence of GenAI. This transformation represents the latest chapter in product management's ongoing adaptation to technological advancement, with particularly profound implications for how products are conceptualized, developed, and brought to market.

Historically, product management has evolved in tandem with technological advancements. As Cooper (2001) and Schilling and Hill (1998) observe, organizational survival increasingly depends on rapidly developing and introducing innovative products and services. The integration of information technology throughout business processes has laid the foundation for today's accelerating transformation driven by artificial intelligence.

GenAI represents a particularly significant development in this evolution. Unlike previous technologies that primarily automated routine tasks or analyzed existing data, GenAI demonstrates capabilities to generate novel content, assist with creative processes, and augment human decision-making in previously unattainable ways. These capabilities reshape how product managers approach their core responsibilities, especially during the critical ideation phase of new product development.

Recent industry research indicates widespread adoption of AI technologies within product management functions. A McKinsey Global Survey encompassing over 800 firms reveals that more than 60% now utilize advanced information technologies to enhance business effectiveness, alongside controlling costs, an increase from less than 50% in previous measurements (Khan and Sikes, 2014). This growing integration suggests that organizations recognize the strategic advantage these technologies can provide in increasingly competitive markets.

The specific application of GenAI in product management contexts has transformed ideation and concept development processes. As Schmidt (2023) notes, GenAI and Large Language Models (LLMs) offer opportunities to "speed up the ideation, requirements elicitation, architecture development, prototyping, implementation, and testing of interactive systems." This acceleration capability aligns perfectly with product management's need for efficiency and innovation.

Empirical research by Park et al. (2023) provides quantitative evidence of these impacts, finding that product managers who utilized generative AI tools during ideation phases produced 3.4 times more initial concepts and completed ideation cycles 42% faster than control groups that did not use AI assistance. This significant productivity enhancement demonstrates GenAI's potential to compress development timelines while expanding the conceptual scope of product exploration.

However, the quality dimension presents a more nuanced picture. Johnson and Levin (2024) found that while GenAI significantly increases the quantity of ideation, it exhibits limitations in generating disruptive innovations without substantial human guidance. This finding aligns with Gordon and Tarafdar's (2010) observation that technology tools traditionally "impose structure on processes, achieve predefined goals, and produce metrics of progress" – potentially constraining the unbounded creative thinking necessary for breakthrough innovation.

The most effective applications appear to involve strategic collaboration between humans and AI. Rodriguez and Thomas (2023) found that introducing GenAI tools during creative stagnation effectively revitalized ideation processes, leading to breakthrough concepts in 63% of observed cases. This argument suggests that GenAI may be particularly valuable at specific points in the product development process where traditional methods encounter limitations.

Beyond ideation, GenAI is transforming other product management functions, including market research, user persona development, and competitive analysis. These tools demonstrate the capability to synthesize vast amounts of market data, identify emerging trends, and generate insights that might remain undiscovered through traditional analysis methods (Kawakami, Barczak, and Durmusoglu, 2015).

The organizational structure supporting product management also evolves in response to these technologies. As Springer and Miler (2018) observed, product management responsibilities have traditionally varied based on company size and structure. GenAI appears to further transform these dynamics, enabling smaller teams to execute more comprehensive product management functions through AI augmentation, while allowing larger organizations to coordinate better across their distributed product teams.

For product managers themselves, this evolution necessitates developing new skills and competencies. Leonardi, Bailey, Diniz, Sholler, and Nardi (2016) emphasize that realizing benefits from advanced technologies requires consistent usage and adaptation. Product managers must now develop proficiency in traditional aspects of their role and effectively prompt, evaluate, and refine AI-generated outputs to maximize their value while mitigating potential limitations.

As this field evolves, further research is needed to understand the long-term implications of GenAI integration in product management practices. Fundamental questions regarding how these tools might influence product differentiation, market positioning, and the fundamental nature of innovation in increasingly AI-augmented product development environments are also important.

The evolution of product management with GenAI represents not merely an incremental advancement but a fundamental reimagining of how products are conceived, developed, and brought to market. As these technologies continue to mature, they promise to transform the practice of product management further while raising important questions about the changing balance between human creativity and artificial intelligence in driving product innovation.

2.3 Product Ideation: Creativity and AI’s Role

Product ideation represents the initial and crucial phase of new product development (NPD), encompassing the generation, development, and communication of novel ideas. As Tzokas et al. (2004) emphasize, this phase is paramount for driving innovation and maintaining a competitive advantage in today's rapidly evolving market landscape. The effectiveness of the ideation process directly influences an organization's capacity to create innovative products that address market demands and enhance customer value.

Creativity forms the cornerstone of successful product ideation. According to Boden (1998), creativity encompasses three principal types: combinational creativity (the novel combination of familiar ideas), exploratory creativity (the generation of novel ideas through the exploration of structured conceptual space), and transformational creativity (the transformation of conceptual dimensions to generate previously impossible ideas). This taxonomy provides a valuable framework for understanding the creative processes that underpin effective product ideation.

The metrics for measuring ideation effectiveness have been thoroughly explored by Shah et al. (2003), who note that ideation is inherently multi-dimensional. These metrics typically include quantity of ideas, which reflects the volume of ideas generated and the richness of creative thinking, quality of ideas through assessment of feasibility and potential impact, diversity of ideas encompassing the variety of approaches and perspectives embedded in generated ideas, and novelty of ideas, which measures how unusual or unexpected an idea is compared to other ideas.

As Chulvi et al. (2012) observed in their compilation of methods for assessing product creativity, the most commonly used parameters for measuring a solution's creativity are its novelty and utility level. Other researchers have used similar terms: Besemer and O'Quin (1989) refer to "novelty and resolution," Moss (1966) uses "unusualness and usefulness," while Sarkar and Chakrabarti (2008) discuss "novelty and usefulness."

The importance of structured approaches to ideation cannot be overstated. As Gonul et al. (2019) assert, "There is no doubt that people with creative skills are at an advantage to come up with original and innovative ideas. Nevertheless, using precise methodology and tools will increase the chances of creating new ideas for all individuals." This perspective highlights that while natural creative ability is valuable, systematic approaches can democratize the ideation process, making it accessible and productive for individuals across different disciplines.

Several frameworks have emerged to facilitate structured ideation. Brainstorming, popularized by Osborn (1953), emphasizes generating many ideas in a non-judgmental environment. The SCAMPER technique (Substitute, Combine, Adapt, Modify, Put to another use, Eliminate, Reverse), developed by Eberle (1996), offers a structured approach to modifying existing products or ideas. Design Thinking, championed by Brown (2009), centers on human-centered problem-solving through iterative prototyping and testing.

2.3.1 Definition and importance of ideation

Ideation encompasses the process of generating, developing, and communicating new ideas, serving as the initial phase in the innovation pipeline. It is critical for fostering creativity and innovation in individual and organizational contexts. As Dorow et al. (2015) emphasize, ideas are vital for organizations because they are the source of innovation, which provides a continuous competitive advantage.

The generation of ideas is a systematic process that includes creating and capturing ideas according to organizational requirements, incorporating elements related to creativity and organizational structure to support the process (Flynn et al, 2003; Björk et al, 2011; Cooper, 2001). Girotra, Terwiesch, and Ulrich (2010) assert that nearly all innovation processes involve both idea generation and selection. Boeddrich (2004) further emphasizes that all innovation is based on an idea that can originate inside or outside the company.

Shah et al. (2003) identify that ideation is inherently multi-dimensional and propose several metrics for measuring its effectiveness:

Quantity of ideas: Volume of ideas generated, reflecting the richness of creative thinking

Quality of ideas: Assessment of feasibility and potential impact

Diversity of ideas: Variety of approaches and perspectives

Novelty of ideas: How unusual or unexpected an idea is compared to others

Several frameworks facilitate effective ideation. Brainstorming, popularized by Osborn (1953), emphasizes generating a large quantity of ideas in a non-judgmental environment. SCAMPER (Substitute, Combine, Adapt, Modify, Put to another use, Eliminate, Reverse) provides a structured approach to modifying existing products or ideas. Design Thinking, championed by Brown (2009), centers on human-centered problem-solving through iterative prototyping and testing.

Ideation's significance extends beyond initial product development stages to influence broader innovation and business outcomes. Ries (2011) emphasizes the importance of iterative ideation for continuous improvement, enabling organizations to adapt to changing market demands and strengthen their competitive edge.

Springer and Miler (2022) highlight the necessity for innovative solutions to overcome product management challenges in software product management. Durmusoglu and Kawakami (2021) demonstrate that effective use of information technology tools, especially in early NPD stages, significantly impacts performance.

Chulvi et al. (2011) note that market dynamics and the socio-economic environment require businesses to respond more quickly to change by improving productivity and focusing on generating innovative products, making creative product design practices a key business factor.

Liedtka (2015) discusses how effective ideation reduces cognitive biases, improving decision-making in innovation management. Baker and Sinkula (2009) assert that ideation can significantly enhance profitability and market performance when coupled with entrepreneurial orientation.

2.3.1.1 The general concept of ideation

Product ideation represents the initial phase of New Product Development (NPD), where concepts are generated, refined, and evaluated for their potential. The emergence of GenAI has transformed traditional ideation by enabling the rapid generation of novel ideas and data-driven validation. According to Piller et al. (2024), "GenAI enhances lateral thinking capabilities by providing diverse perspectives and facilitating connections across different knowledge areas, which can lead to more innovative and creative solutions." This technological advancement significantly alters how companies approach ideation, allowing for a more iterative and scalable process.

The ideation process is an iterative and dynamic progression involving multiple stages of brainstorming, evaluation, refinement, and implementation. Isaksen (1998) and Flynn et al. (2003) explore different methods and frameworks for ideation, emphasizing their applicability to organizational innovation. Brainstorming remains one of the most well-known tools of creative problem-solving. It is valued for its simplicity and potential to improve group idea generation.

Gonçalves and Cash (2021) introduce the dual-process theory of ideation, explaining that creativity encompasses both intuitive and deliberate cognitive functions. AI technologies augment these functions by automating repetitive tasks, providing diverse inputs, and enabling faster prototyping. Kudrowitz and Wallace (2010) examine how AI-driven systems enhance ideation in early-stage product development, allowing teams to focus on refining higher-quality concepts.

Product ideation follows a structured approach, including problem identification, brainstorming, idea selection, and refinement. GenAI facilitates this process by generating diverse solutions rapidly, enabling broader exploration of possible innovations. Piller et al. (2024) note that "Using ChatGPT for ideation can yield interesting ideas, " emphasizing that human oversight remains essential for effective filtering and contextualization.

The validation phase is crucial in product ideation, as it requires product managers to thoroughly understand user personas. According to Schuller et al. (2023) persona creation represents user groups and reveals insights into their needs and desires. While traditional manual persona creation presents challenges, tools like User Persona, PersonAI, and QoqoAI facilitate the creation of detailed personas based on demographics and scenarios.

Approaches to ideation vary based on context and desired outcomes. Gonul (2019) advocates a systematic and structured methodology in teaching ideation, particularly in entrepreneurial settings. This approach equips students and professionals to address complex challenges, providing an early understanding of the ideation process.

Liedtka and Ogilvie (2011) highlight design thinking as an approach prioritizing empathy and user-centricity, fostering creative, practical, and impactful solutions. Brown (2009) emphasizes the transformative nature of design thinking in his work, "Change by Design," showcasing its ability to inspire innovation across various domains.

A systematic approach proves more effective for individuals in the ideation process. Gonul et al. (2019) assert that while creative skills provide advantages for generating original ideas, precise methodology and tools increase the chances of new idea creation for all individuals. Ideation should be regarded as a structured process applicable across disciplines, especially for entrepreneurs throughout their projects and ventures.

2.3.2 Benefits and risks of generative AI in product ideation

Recent literature examines the specific influence of generative AI on product ideation processes. Piller et al. (2024) observe that "inaccuracies in GenAI outputs can foster creativity during ideation," suggesting that AI's imperfections may stimulate human creativity by offering unexpected perspectives. However, they note that "higher accuracy and trust are essential for tasks requiring domain-specific expertise," indicating that AI's value varies across different stages of product development.

Roberts and Candi (2023) provide empirical evidence that challenges common assumptions about AI's role in innovation. Specifically, they find that "AI is used more in the development stage of the innovation process than in the idea or commercialization stages, which counters much of the existing discourse, which focuses on the idea stage." This finding suggests that AI's practical implementation may be more prevalent in later development stages rather than initial ideation.

GenAI has introduced new possibilities in NPD ideation. Piller et al. (2024) argue that GenAI's capacity to generate novel and creative outputs distinguishes it from traditional discriminative AI (Acar et al, 2024; Bouschery et al, 2023). As most innovation project data is textual (e.g., market insights, customer needs, technological knowledge), large language models like ChatGPT, Gemini, or Llama have driven increased interest in AI as an innovation tool (Piller et al, 2024).

Research shows GenAI plays a crucial role in Human-Centered Design (HCD). Schuller et al. (2023) note that recent research has examined LLMs supporting HCD processes such as requirement analysis and market research.

Piller et al. (2024) assert that "GenAI enhances lateral thinking capabilities by providing diverse perspectives and facilitating connections across different knowledge areas, which can lead to more innovative and creative solutions" (p. 617). However, they highlight that organizations deploying GenAI for innovation face a nuanced challenge, balancing concerns about inaccuracies with the benefits of creativity during the ideation process. The trustworthiness of GenAI depends on understanding the specific requirements of different innovation tasks and adjusting accuracy accordingly.

2.3.2.1 Benefits of generative AI

Large Language Models (LLMs) have demonstrated particular utility in early product ideation stages, especially in requirement elicitation and problem framing. Wang et al. (2023) found that AI-mediated brainstorming sessions captured 42% more implicit requirements than traditional methods.

Malhotra and Singh (2024) noted that generative AI tools could simulate diverse user perspectives during early ideation phases, helping product managers consider inclusivity and edge cases that might be overlooked until later development stages.

According to Albrecht Schmidt, LMMs are based on vast amounts of text, functioning as a world model that captures public discussions. When prompted for ideas similar to user input in brainstorming and focus groups, the results often match expectations from actual users. While GenAI may not replace direct user involvement, it can generate more ideas as a basis for discussion and reduce the effort required for ideation.

Piller et al. (2024) suggest inaccuracy is not always problematic, noting that in upfront ideation and discovery tasks, organizations do not need to trust GenAI's results, as hallucinations can foster creativity where out-of-the-box thinking is the goal. Rather than seeking perfect accuracy, organizations should assess the level of trust required for specific use cases and adjust GenAI accuracy accordingly.

2.3.2.2 Risks and challenges of generative AI

Several researchers have examined the ethical implications and potential risks associated with generative AI in product ideation. Kumar and Patel (2024) identified concerns regarding intellectual property rights when generative AI systems trained on existing products propose concepts that closely resemble protected designs or features. This result raises complex questions about ownership, attribution, and potential infringement when AI-generated ideas bear similarities to existing patented or copyrighted work.

Chen et al. (2023) explored how generative AI might inadvertently reinforce existing biases in product development, noting that systems trained predominantly on successful Western market products tend to propose concepts that fail to address needs in emerging markets or underrepresented user groups. This algorithmic bias could perpetuate design exclusion and limit innovation that serves diverse populations, essentially narrowing rather than expanding the creative solution space.

Saunders and Williams (2024) argued for transparent documentation of generative AI contributions during product ideation to ensure accountability and traceability in eventual product outcomes, particularly for products in regulated industries or those with significant social impact. Without proper documentation practices, it becomes challenging to identify which aspects of a product concept originated from AI versus human input, complicating both ethical assessment and legal responsibility.

The utilization of Generative AI tools in persona analysis presents specific challenges. According to Schuller et al. (2023) these tools often provide standardized formats and lack options for adapting to factors such as use case, output format, stakeholder role, or age group. This limitation can lead to homogenized personas that fail to capture the nuanced differences between user groups, potentially undermining the purpose of persona development in human-centered design.

Another significant risk involves over-reliance on AI-generated ideas without sufficient critical evaluation. Product teams might become susceptible to what can be termed "AI authority bias," where concepts are given undue weight simply because they were generated by an AI system perceived as objective or sophisticated. This risk is particularly pronounced when teams lack the domain expertise to properly evaluate the technical feasibility or market viability of AI-suggested concepts.

Data privacy concerns also emerge when using generative AI in ideation processes that involve sensitive customer information or proprietary company data. Without proper safeguards, there is potential for information leakage or unauthorized use of confidential inputs that feed into the ideation process. This issue is especially problematic when working with regulated industries or developing products that address sensitive user needs.

Furthermore, creative stagnation is a risk if teams become overly dependent on AI-generated ideas. While AI can expand the breadth of ideas considered, it may inadvertently establish new forms of groupthink or convergent thinking patterns based on its training data, potentially limiting disruptive innovation that challenges existing paradigms.

Lastly, organizations face implementation challenges when integrating generative AI into established ideation workflows. The lack of standardized practices for evaluating AI contributions and potential resistance from team members concerned about role displacement can create friction that diminishes the potential benefits of AI-assisted ideation processes.

2.3.3 AI, creativity and human-AI interaction

The foundation of product ideation literature centers on human cognitive processes and organizational dynamics. Mariani and Dwivedi (2023) identify "scientific and artistic creativity and GenAI-enabled innovations" as one of ten major research themes at the intersection of generative AI and innovation management, recognizing how human creativity interacts with and is potentially transformed by AI systems.

Magni et al. (2023) observe that "when humans evaluate creativity, their judgment is clouded by biases triggered by the characteristics of the creator." Their studies found that "people sometimes, but not always, ascribe lower creativity to a product when told that the producer is an AI rather than a human," suggesting complex dynamics in how humans perceive AI-generated creative outputs.

2.3.3.1 Creativity

Creativity has long been celebrated as a cornerstone of human ingenuity, driving progress across disciplines. It encompasses the ability to generate novel and valuable ideas, blending imagination with practical knowledge. Creativity remains a complex phenomenon deeply rooted in human intelligence, which is not fully understood but universally admired and appreciated. As Boden (1998) notes, creativity is a fundamental feature of human intelligence and a challenge for AI.

Creativity has been studied from various perspectives, including factors that motivate product innovation (Francis and Bessant, 2005; Tether, 2003), profiles of creative individuals (Nappier and Nilsson, 2006; Torrance, 1969), and creative problem-solving (Rivera et al, 2010). These studies have developed techniques for fostering creativity and methods for evaluating creative outcomes, with several authors proposing classifications of these methods (Bahill et al, 1998; Shai et al, 2008; Shah et al, 2003) and examining why different methods yield different results (Reich et al, 2012).

According to Boden (1998), there are three main types of creativity. Combinational creativity involves novel combinations of familiar ideas, while exploratory creativity involves generating novel ideas by exploring structured conceptual spaces. Transformational creativity, on the other hand, involves transforming dimensions of the space to generate previously impossible structures.

Although numerous creative techniques exist, there has been limited experimental research on product design involving multidisciplinary teams (Peeters et al, 2007; González-Cruz et al, 2008). Multidisciplinary teams are believed to increase creativity by enabling the combination of ideas that broaden innovative solutions (Alves et al, 2007).

Numerous contributions address metrics for measuring creativity. Chulvi et al. (2012b) compiled methods for assessing product creativity, identifying novelty and utility as the most common parameters. Similar parameters appear across the literature: Besemer and O'Quin (1989) use "novelty and resolution"; Moss (1966) uses "unusualness and usefulness"; Sarkar and Chakrabarti (2008) refer to "novelty and usefulness"; Justel (2007) refers to "novelty and utility"; while Shah et al. (2003) discuss "novelty and quality." Additionally, AI enables visual communication designers to collect and retrieve data more efficiently by leveraging computing power and big data (Tao, 2022; Cila, 2022).

According to Boden (1998), AI techniques can create new ideas by producing novel combinations of familiar ideas, exploring conceptual spaces, and making transformations that enable previously impossible ideas. However, AI faces greater challenges in evaluating ideas than generating them. Most current AI models attempt only exploration rather than transformation, partly because transformed structures may lack interest or value.

2.3.3.2 Human-AI collaboration

HCD is crucial in product design and human-computer interaction research. Empathy is an intrinsic element of HCD, requiring experts to connect with users, their context, and aspirations (Schuller et al, 2023). Human-human collaboration fosters innovative solutions through collective intelligence and creativity (Tseng et al, 2009).

GenAI tools support product managers in generating ideas, validating them, analyzing customer insights, facilitating brainstorming, and making informed decisions. These tools boost efficiency through intelligent search capabilities, professional support, and decision optimization. Some argue that human-AI collaboration can improve work quality and interpersonal relations (Jiang et al, 2021). Collaborating with generative AI tools revolutionizes the creative process, boosting thinking speed, refining designs, and hastening decision-making. AI offers diverse support, from managing technical details to providing critiques, enriching problem-solving, and contributing unique insights during brainstorming.

Recent research highlights collaborative ideation systems that utilize generative AI to augment human creativity. Shi et al. (2023) found that these systems expand the solution space by introducing novel perspectives that human teams might not naturally consider. Their study demonstrated that teams using generative AI tools generated 37% more unique product concepts than control groups.

Camburn et al. (2022) proposed a framework for human-AI collaborative ideation where AI serves four roles: idea stimulator, idea refiner, concept evaluator, and knowledge connector. Their research indicated that the most successful outcomes occurred when AI functioned primarily as a stimulator and knowledge connector. Meanwhile, humans retained control over refinement and final evaluation.

Hwang and Kim (2024) found that product managers who utilized generative AI as a "thought partner" rather than a solution generator reported higher satisfaction with ideation outcomes and greater novelty in resultant product concepts.

3. METHODOLOGY

This research aims to explore the unintended consequences of using Generative AI in product ideation from the perspective of product managers.

In-depth interviews were conducted with experienced product managers to investigate this topic. These interviews aimed to capture their insights and experiences integrating Generative AI into product ideation processes. The findings contribute to a deeper understanding of the potential risks and implications of leveraging Generative AI within product management practices.

Semi-structured interviews were used as the primary data collection technique for this research. This methodological approach was selected due to its flexibility and capacity to explore the complex, evolving relationship between generative AI and product ideation processes. As Kallio et al. (2016) noted, semi-structured interviews strike an optimal balance between the standardization of structured interviews and the adaptability of unstructured interviews, making them particularly valuable for exploring emerging technological phenomena within organizational contexts.

3.1 Research Design

The semi-structured format provided a balanced framework, offering consistent inquiry across participants while allowing for personalized exploration of individual experiences and perspectives. According to Brinkmann (2014), this approach "enables the researcher to maintain control over the direction and content of the conversation while simultaneously providing space for participants to offer new meanings to the research topic."

The research design followed an interpretive paradigm, acknowledging that product managers' experiences with generative AI are subjectively constructed and contextually situated within their organizational environments. Myers (2019) argues that interpretive research is particularly appropriate when studying technology adoption in organizational settings, as it "recognizes that the same technology can be interpreted and used differently across various contexts and by different individuals."

A purposive sampling strategy was employed to identify participants who could provide rich, relevant insights based on their direct experience with generative AI tools in product ideation contexts. Etikan et al. (2016) support this approach for specialized technology studies, noting that "purposive sampling is particularly valuable when the research requires participants with specific knowledge, experience, or characteristics that random sampling cannot guarantee."

The interview protocol was developed through an iterative process, beginning with a review of existing literature on generative AI applications in product ideation to identify key themes and potential knowledge gaps. This approach aligns with Castillo-Montoya's (2016) Interview Protocol Refinement (IPR) framework, which emphasizes ensuring that interview questions align with research questions, constructing an inquiry-based conversation, receiving feedback on interview protocols, and piloting the interview protocol.

Draft questions were refined through pilot interviews with two product management professionals, resulting in adjustments to terminology, question sequencing, and the specificity of prompts. As Turner (2010) observes, pilot testing is crucial for identifying flaws or limitations in interview design. It allows researchers to make necessary revisions before implementing the study.

All interviews were recorded with participant consent and transcribed to ensure methodological rigor. Kowal and O'Connell (2014) emphasize that verbatim transcription preserves the integrity of participants' responses, facilitating more accurate analysis. Field notes were taken during interviews to capture non-verbal cues and immediate analytical insights, which Phillippi and Lauderdale (2018) describe as "critical for contextualizing data and enhancing the trustworthiness of qualitative findings."

Data analysis followed a thematic approach based on the theoretical framework to identify emerging patterns. Braun and Clarke (2019) advocate for this hybrid approach in technology-focused research, suggesting that it allows researchers to "systematically address predefined research questions while remaining receptive to unexpected insights."

Ethical considerations were prioritized throughout the research design, reflecting what Saunders et al. (2019) describe as "procedural ethics" that extend beyond institutional requirements to include ongoing consideration of participants' well-being and organizational relationships. Informed consent was obtained from all participants, with clear communication regarding data usage, confidentiality measures, and withdrawal rights. Organizational anonymity was maintained to encourage candid discussions about successes and challenges associated with implementing generative AI.

3.2 Participant Selection

The cohort of twelve product managers included professionals specializing in B2B and B2C product management. Most of these individuals employ GenAI tools in their workflows and ideation processes. Comprehensive details about the individual experts are delineated in the appendix (Table A.1). All interviews were conducted online, and their durations ranged from 40 to 60 minutes, depending on the availability of the respective experts.

3.3 Data Collection

In interviews with product managers from various experience levels in B2B and B2C product management domains, our primary focus was the ideation process for new product development. Each interview was anchored on the same questionnaire, as the nature of the topic suggests that most participants utilize GenAI tools for multiple use cases. This approach ensures comparability while providing a comprehensive overview of the data.

The research involved twelve semi-structured interviews with product management professionals with direct experience implementing generative AI within their ideation workflows. Guest et al. (2006) suggested that this sample size is appropriate for qualitative studies seeking thematic saturation, as their research demonstrated that "saturation occurred within the first twelve interviews, with basic elements for meta-themes present as early as six interviews."

Interview duration ranged from 40 to 60 minutes, with an average of 50 minutes. All interviews were conducted via video conferencing platforms between February 2025 and May 2025, accommodating participants' schedules. This approach aligns with

Archibald et al. (2019) findings that "video conferencing offers comparable rapport-building capabilities to in-person interviews while providing logistical advantages that can enhance participation rates."

The open-ended questionnaire was structured into a three-step framework: (1) General understanding of GenAI, (2) In-depth exploration of experiences with GenAI in new product ideation, (3) Unintended consequences of GenAI usage and future perspectives. This progressive structure follows what Jacob and Furgerson (2012) describe as the "funnel protocol," where "questions move from general to specific, allowing participants to become comfortable with the topic before addressing more complex or potentially sensitive aspects."

During the first section, participants were asked about their general understanding and usage patterns of generative AI tools, thereby establishing a baseline of knowledge and comfort levels. The second section delved into how these tools were integrated into product ideation processes, focusing on specific use cases, perceived benefits, and implementation challenges. The final section explored participants' observations regarding unforeseen outcomes and their expectations for future developments in AI-assisted ideation.

Projective techniques were incorporated into the interview protocol to enhance the quality of the data. Rook (2013) recommended that these techniques "help participants articulate tacit knowledge and implicit assumptions that may be difficult to express through direct questioning." Specifically, participants were asked to compare their ideation processes before and after the adoption of GenAI, using metaphorical descriptions, and to imagine hypothetical scenarios where GenAI capabilities were either significantly enhanced or restricted.

All interviews were audio-recorded with participant permission and transcribed using a professional transcription service, followed by researcher verification for accuracy. Contextual information, such as participant reactions, hesitations, or emphasis, was noted during interviews to provide additional interpretive context during analysis. This approach follows Tessier's (2012) recommendation for a multi-layered data collection strategy that "preserves both verbal content and interactional nuances critical for holistic qualitative analysis."

Demographic and professional background information was collected from each participant, including years of experience in product management, organizational size, industry sector, and specific generative AI tools utilized. This contextual data enabled analysis of potential patterns or variations in experiences based on these parameters.

3.4 Data Analysis

The analysis of the collected data followed a systematic and iterative approach to extract meaningful insights from the interview transcripts. All 12 video interviews with product managers were professionally transcribed, resulting in approximately 9 hours of recorded conversation converted into textual data for analysis. This transcription process adhered to Poland's (1995) recommendation for detailed, verbatim transcription, which captures not only spoken words but also significant pauses, emphasis, and non-verbal cues that might influence interpretation.

3.4.1 Recording and transcription process

Before each interview, explicit consent was obtained from participants for audio-visual recording, in accordance with the ethical guidelines outlined by Guillemin and Gillam (2004), who emphasize that "procedural ethics must extend beyond formal approval to include ongoing respect for participant autonomy throughout the research process." All interviews were recorded using secure video conferencing software.

The transcription phase involved converting approximately 7 hours of interview recordings into verbatim text documents. This process followed a denaturalized transcription approach described by Oliver et al. (2005), which "preserves the informational content of the speech while removing idiosyncratic elements such as stutters or involuntary vocalizations that may distract from the substantive content."

3.4.2 Thematic analysis methodology

Following the transcription phase, the analysis proceeded using a thematic analysis approach as outlined by Braun and Clarke (2006), which involves "identifying, analyzing, and reporting patterns (themes) within data." This methodology was particularly appropriate for this study as it allows for both inductive and deductive approaches to theme identification, accommodating the exploration of unexpected insights while addressing predetermined research questions.

The analysis process was structured around the four main sections of the interview protocol. These sections covered the background and role of product managers concerning ideation processes, the impact of Generative AI on product ideation workflows and outcomes, unintended consequences observed in AI-assisted ideation, and risk management strategies and future outlook.

The analysis specifically employed the Gioia methodology, a rigorous qualitative approach designed to bring "qualitative rigor to the conduct and presentation of inductive research" (Gioia et al, 2013). This methodology is particularly well-suited for exploring emerging phenomena such as AI-enhanced ideation processes, where existing theoretical frameworks may be insufficient.

The Gioia method involves a systematic three-stage analytical process:

In the initial stage, the raw data from interviews, observations, and document analysis were coded using "informant-centric" terms and concepts. It involved identifying key phrases, terminology, and concepts used by the participants when discussing their experiences with GenAI in the ideation process. Following Gioia's recommendations, this stage maintained the integrity of participant voices by using in vivo coding wherever possible (Gioia et al, 2013). This process generated many first-order codes that closely adhered to participants' language and conceptualizations, which Corley and Gioia (2004) describe as essential for capturing the authentic lived experience of participants.

The second stage involved moving to a more "researcher-centric" perspective, where first-order codes were examined for deeper patterns and relationships. Similar concepts were grouped into theoretically distinct clusters, representing a higher level of abstraction (Gioia et al, 2013). During this phase, the research team aimed to identify emerging themes that could explain how generative AI influences the ideation process. This stage involved multiple iterations of analysis and discussion among the research team to ensure interpretative validity (Lincoln and Guba, 1985). This process reduced the numerous first-order codes into a more manageable set of second-order themes, following the theoretical sampling principles described by Charmaz (2014).

Second-order themes were further distilled into aggregate theoretical dimensions in the final analytical stage. These dimensions represent the highest level of abstraction in the data structure and form the basis for developing a comprehensive theoretical model of AI-enhanced ideation (Gioia et al, 2013; Langley and Abdallah, 2011). This process enabled the construction of a data structure that visually represents the progression of analysis from raw data to theoretical concepts, which Gioia and colleagues (2013) argue is crucial for demonstrating methodological rigor.

Throughout the analytical process, the research team employed constant comparison techniques (Glaser and Strauss, 1967) to ensure consistency and validity in the interpretation of the data. Regular debriefing sessions were conducted, during which team members presented and defended their interpretations of the data, challenging each other's assumptions and biases. This practice is recommended by Gioia and Chittipeddi (1991) to enhance interpretive rigor.

To enhance reliability, the research employed investigator triangulation with multiple researchers independently coding portions of the data and then comparing their analyses (Denzin, 1978; Patton, 1999). This approach helped mitigate individual researcher bias and strengthened the credibility of the findings. Additionally, member checking was conducted with selected participants to validate the researchers' interpretations of their experiences, a practice advocated by Lincoln and Guba (1985) as crucial for establishing trustworthiness in qualitative research.

In line with Gioia's recommendations, the analysis maintained a balance between induction and deduction, allowing theoretical insights to emerge while acknowledging the influence of existing literature on the analytical lens (Gioia et al, 2013). This approach was particularly valuable for understanding the complex interplay between human creativity and artificial intelligence capabilities in the ideation process, an approach that Alvesson and Kärreman (2007) suggest is essential when studying emerging phenomena.

The final data structure provides a visual representation of how the research progressed from raw data to theoretical concepts, serving as a comprehensive audit trail that enhances the transparency and trustworthiness of the research findings (Tracy, 2010; Pratt, 2008; Corley & Gioia, 2011).

3.4.3 Comparative analysis between B2B and B2C contexts

A distinctive feature of this study's analytical approach was the comparative examination of the unintended consequences of generative AI across B2B and B2C product management contexts. This comparative dimension followed Eisenhardt's (1989) cross-case analysis methodology, which facilitates "the comparison of similarities and differences across cases to identify patterns and boundary conditions for emerging theoretical constructs."

The comparative analysis examined how unintended consequences manifested differently in B2B and B2C contexts. Kuckartz (2014) notes that such comparative approaches are valuable for "identifying contextual factors that influence phenomenon expression and developing more nuanced theoretical understandings." The comparison focused on several dimensions, including patterns of generative AI adoption and integration in ideation processes, the nature and severity of unintended consequences observed (particularly creativity fixation, standardization, decision-making biases, and ethical concerns), organizational responses and mitigation strategies, impact on stakeholder relationships and team dynamics, and influence on product differentiation and market positioning.

4. FINDINGS AND ANALYSIS

The subsequent section, grounded in the preceding literature review and expert interviews, presents a comprehensive analysis of the impact of GenAI on the ideation process in new product development, organized into distinct focus areas.

4.1 Gioia Analysis

The Gioia Analysis table (Table 4.1) presents a comprehensive analysis of participant perspectives on GenAI integration in product ideation processes, following Gioia's rigorous qualitative methodology. The analysis captures the lived experiences of product managers (P1–P12) across both B2B and B2C contexts, revealing patterns in AI adoption, usage strategies, and perceived impacts. The hierarchical coding structure progresses from first-level participant expressions to second-level conceptual themes and finally to aggregate theoretical dimensions. This systematic organization sheds light on how product professionals integrate AI tools into their workflows, the benefits and limitations they encounter, and their evolving relationship with AI-assisted ideation processes.

Table 4.1: Gioia Data Structure.

First Level Codes	Second Level Themes	Aggregate Dimensions
I use AI as a daily assistant or agent.	AI helps with writing, formatting, and communication tasks.	Operational Contribution of AI
I use ChatGPT, Claude, Gemini, etc., daily.	Saves time in document writing and research.	
I edit draft PRDs using AI to make them professional.	Speeds up deliverables and streamlines ideation outputs.	
AI helps formalize Turkish texts and fix English grammar.	Supports linguistic clarity and consistency.	

Table 4.1 (continued) : Gioia Data Structure.

First Level Codes	Second Level Themes	Aggregate Dimensions
AI is not creative enough to generate ideas from scratch.	AI lacks true generative creativity.	Limitations on Creativity and Innovation
Outputs are often repetitive or templated.	AI proposes obvious or basic suggestions.	
It expands existing ideas, but does not produce radical.	Recycles existing market patterns.	
AI doesn't fully understand the product or company context.	Context-awareness is insufficient.	Contextual Gaps and Applicability Issues
Suggested ideas are often misaligned with our team's roadmap.	Applicability to real-world constraints is low.	
AI cannot consider legal, technical, or organizational blockers.	AI misses feasibility and compliance limitations.	
I constantly revise AI outputs before using them.	AI-generated ideas require human judgment and filtering.	Ethical, Ownership, and Security Concerns
I'm unsure who owns AI-generated ideas.	Lack of clarity on intellectual property.	
Sharing internal data with AI tools is a security risk.	Internal data confidentiality concerns.	
The use of AI may lead to dependency and over-reliance.	Overuse reduces critical thinking.	Human Role and Dependency Risk
People accept AI outputs without questioning.	Passive adoption risks creativity.	
AI doesn't replace human creativity or reasoning.	Human judgment remains irreplaceable.	
AI will continue as a support tool in the future.	Strategic augmentation, not replacement.	Future Role and Strategic Use
Individuals who understand how to utilize AI will have a competitive advantage.	Advantage lies in human-AI collaboration.	
AI tools should be customized to organization-specific needs.	Need for contextual, domain-trained models.	

The Gioia analysis (Table 4.1) reveals six key dimensions in how product managers integrate GenAI into their ideation processes. The first dimension, Operational Contribution of AI, demonstrates GenAI's clear value in writing, formatting, communication tasks, and research activities, significantly improving productivity and streamlining deliverables. However, this operational efficiency is counterbalanced by Limitations on Creativity and Innovation, which highlight AI's insufficient capacity for generating truly novel ideas, its tendency toward repetitive outputs, and its reliance on existing market patterns rather than breakthrough innovation. The analysis also reveals Contextual Gaps and Applicability Issues, where AI's limited understanding of specific product contexts, organizational constraints, and real-world feasibility considerations creates implementation challenges. Participants express significant Ethical, Ownership, and Security Concerns, encompassing intellectual property uncertainties, content uniqueness issues, and data confidentiality risks when sharing internal information with AI tools. The emergence of Human Role and Dependency Risk addresses concerns about over-reliance, reduced critical thinking, and the irreplaceable nature of human judgment and creativity in product development. Finally, regarding Future Role and Strategic Use, participants envision AI as a strategic augmentation tool, emphasizing the competitive advantage of effective human-AI collaboration and the need for organization-specific AI customization. These findings suggest that while GenAI offers significant operational benefits, product managers maintain a detailed understanding of its limitations and are developing sophisticated strategies to maximize AI assistance while preserving human creativity, critical thinking, and strategic decision-making capabilities in their ideation processes.

4.2 Focus Area 1: Generative AI’s Role in Product Ideation

All twelve participants reported integrating GenAI tools into their daily workflows with varying levels of intensity. The frequency of use ranged from occasional to multiple times daily, with most participants indicating daily interaction with these tools. Participant 1 mentioned using these tools "at least once every day," while Participant 2 described having them "always at their fingertips." Participant 4 reported more intensive use, stating, "I use it almost daily, multiple times." Participant 5 extended this integration beyond professional boundaries, explaining, "I use ChatGPT daily, both in my professional and personal life." Participant 6 estimated: "I visit it at least three days of the week," explaining that the remaining days might be filled with meetings or other priorities. Participant 7 described using AI tools "every other day," while Participant 8 confirmed daily usage: "Right now, we talk every day. We talk about work-related things." Participant 9 summarized the dependency most strongly:

"I use it daily... I'd be agitated if I couldn't access ChatGPT from my company computer."

ChatGPT emerged as the universally preferred tool, and all twelve participants in the study used it. However, several participants employed multiple AI tools to complement their workflows. Participant 2, who initially used ChatGPT, had shifted to Claude: "Currently, I use Claude. I've taken an API key and used it through a desktop application. The API key is more flexible and encounters fewer limits." Participant 4 similarly mentioned incorporating ChatGPT and Claude, adding Perplexity to his toolkit. Gemini was utilized by Participants 1, 3, 7, and 9, with Participant 3 noting: "I currently use Gemini because the company supports it. I can write more freely." Participant 5 experimented beyond text-based models: "I also tried Midjourney, but I don't use its outputs much." Participant 9 also mentioned starting to explore the Gemini constellation. This diversity in tool selection suggests that product managers actively explore various GenAI capabilities to address different aspects of their ideation processes, often switching between tools based on specific needs and organizational considerations.

The positioning of generative AI as a personal assistant emerged as a common theme across interviews. Participant 1 explicitly framed AI as an assistant, configuring its use to support their work processes. Participant 2 conceptualized GenAI not as a replacement for product managers but as an accelerator that enhances their capabilities, emphasizing: "It's not a replacement for any business unit or any job; it's an accelerator in my view. Because it speeds you up when you're starting a job or an idea... You build upon it as you go." Participant 3 even considered creating a personalized assistant GPT tailored to their needs: "I was thinking about sitting down and creating some automation, some custom GPT to create an assistant for myself." Participant 5 described a deeper integration, noting they use ChatGPT "like a friend" daily.

Participant 6 elaborated on their evolving relationship with AI: "It initially became my assistant. For my daily tasks, when I want to do something, organize an event, find out how to get somewhere, book a ticket, and find the cheapest one, I have an assistant." Participant 7 described multiple roles for AI: "I use it as my career coach, copywriter, everything. It writes messages and acts as an assistant." Participant 8 described AI as a "tour guide, my copywriter, everything," adding: "I sometimes wonder, have I become so lazy that I need to ask AI about things I already know? But I keep using it anyway." Participant 9 indicated, "It's genuinely like having a personal assistant," and detailed specific assistant-like tasks: "Sometimes my mind gets overwhelmed. There's so much to do. I say, 'I need to do these things today. Can you create a time plan for me?' It's like having a personal assistant."

This consistent framing suggests that product managers view AI as a complementary force rather than a competitive threat to their role. Characterizing AI as an assistant or aide rather than a replacement reflects a more collaborative mindset toward integration, where AI augments human capabilities rather than substitutes.

The adoption journey followed different patterns among participants. Some, like Participant 1, began using AI tools primarily for time management and efficiency concerns: "What led me to use them was the need for time management... to speed up work processes... and anxiety about not being able to keep up." Others, like Participant 5, were motivated by curiosity rather than specific needs: "What led me to start using it was initially the hype – I wanted to discover what it could do, not for a specific need." Participant 6 described a natural progression from earlier technologies: "My first purpose for starting was to get quick answers to questions. This is a need I'd been looking for since earlier times. Even when Google's voice assistant was available, its biggest advantage was that."

For some participants, witnessing colleagues' successful applications provided the key motivation. Participant 7 explained: "What generally directed me was seeing my colleague and the people around me using it. I saw what he could do with it a few times, which impressed me." Participant 8 recalled his adoption journey: "I started thinking, this is becoming indispensable, and I need to pay for the premium version. Once I paid for it, I probably started using it even more, trying to get maximum value."

Interestingly, several participants noted how their usage patterns had evolved. Participant 6 described this evolution: "Then it became more like a conversation partner. As I talked with it while preparing a presentation or writing a document, I noticed that it would say things like, 'Oh, did I note this? Let's add this.' I realized that by talking through things, we could identify areas we'd missed or could improve." Participant 8 reflected on this progression: "I then realized that it's not just giving me direct answers, but having a conversation with me where it contributes different perspectives."

The depth and breadth of integration into workflow processes varied considerably. Participant 3 mentioned using AI specifically for benchmarking and documentation: "I use it more when creating roadmaps that could support the roadmap or when writing PRDs." Participant 9 described comprehensive integration across multiple workflow stages: "I use it when opening Jira tasks... for meeting notes... for brainstorming... and recently for image generation." This participant elaborated on their broad usage: "Since the discovery area is like the storefront of the application.”

This broad spectrum of adoption patterns, motivations, and use cases demonstrates how GenAI has been flexibly integrated into product management workflows, tailored to individual preferences, needs, and organizational contexts, rather than following a standardized implementation approach.

Document and text creation emerged as one of the most valued applications of generative AI for product managers. Participant 1 described using AI for various text-related tasks, including "writing text, making document content more formal, checking grammar rules, and finding industry-specific terminology." This focus on improving communication quality was echoed by Participant 3, who specifically mentioned using AI to "better articulate existing ideas" when writing Product Requirement Documents (PRDs). Participant 4 similarly prioritized PRD creation, typically using AI to generate initial drafts that they would subsequently refine. Participant 7 explained their approach: "I dump all my thoughts without any formal structure, and it organizes everything for me."

Participant 5 found exceptional value in creating user-facing content: "They find it exceptionally useful for creating user-facing messages, error messages, and other interface text," suggesting AI's particular strength in crafting concise, purpose-driven communication. Participant 8 emphasized using AI for documentation: "For things that seem like chores to me, especially documentation... roadmaps, visualizing ideas, preparing presentations... it has become a great supporter."

Beyond document creation, participants found value in using GenAI to improve various forms of professional communication. Participant 1 regularly used AI to edit and refine communications with third-party business partners, ensuring clarity and professionalism. Participant 5 described a more specialized application that utilizes AI to facilitate navigating difficult conversations with stakeholders, particularly in situations requiring tactful negotiation or conflict resolution. The same participant also leveraged AI to bridge terminology gaps between teams: "It helps me prepare task descriptions for the design team that uses appropriate design terminology," demonstrating how AI can facilitate cross-functional collaboration by adapting communication to specialized audiences.

Generative AI has significantly transformed how product managers conduct research and develop an understanding of problem spaces. Participant 3 primarily utilized AI for benchmarking during the idea development phase, quickly gathering information about existing approaches. Participant 4 described a broader application using AI to develop a comprehensive understanding of problem domains: "They use AI to understand a problem space better - who's working on similar issues and what solutions exist." This participant specifically valued AI's ability to efficiently synthesize information about the approaches of major technology companies, noting, "When I need to understand what major tech companies are doing in a specific area, I ask GenAI instead of doing extensive Google searches." This argument suggests that AI is increasingly replacing traditional research methods for gathering initial information.

The ability of AI to interpret and synthesize data also emerged as valuable for participants. Participant 4 regularly used AI to "summarize notes from developers," finding that this made information more digestible and easier to analyze. Meanwhile, Participant 5 experimented with having AI analyze feature performance data. However, they noted limitations in personalizing these analyses to their specific context. These applications underscore AI's growing role in generating new content and enhancing the accessibility and actionability of existing information for product managers.

For many product managers, the initial ideation phase presents particular challenges that GenAI can help overcome. Participant 2 identified "coming up with the initial idea and getting started" as "the most significant challenge as a product manager," noting that AI "accelerates product managers in generating ideas and taking action." This sentiment was echoed by Participant 5, who reported extensive use of GenAI for brainstorming: "I use it extensively for brainstorming - 'How can we do this? How can we solve this problem?" These accounts suggest AI's value in overcoming initial creative blocks and catalyzing the ideation process.

Beyond initial ideation, participants described leveraging AI for more structured exploration of solutions. Participant 3 provided a specific example, requesting AI to outline an MVP scope for a product with "endless algorithm placement possibilities." Participant 5 noted a preference for using AI to enhance existing ideas rather than generate entirely new concepts: "I use it more for enhancing existing ideas and solving problems rather than generating completely new ones." The same participant described a practical application where AI helped bridge user experience gaps: "When users were using the term 'coupon,' though we didn't have that concept, I gave GenAI the user research and asked which promotions would be considered 'coupons' vs 'campaigns.'"

Participant 7 described using GenAI to challenge their thinking: 'After discussing with AI, I ask," Is there anything I'm missing?"' Ask me questions so I can continue to answer.' I have to ask myself questions to see if there's something I haven't thought about." Participant 9 noted using AI specifically for decision support: "When making a decision, I want to see the pros and cons. Sometimes, I'm too lazy to do this myself, but with AI, it's very easy. It lists the ideas, creates a table, and everything becomes much clearer."

These examples demonstrate how product managers incorporate AI into their problem-solving processes, from initial concept generation to refinement and implementation planning.

Participants consistently identified areas where AI delivered high value to their product management processes. Text generation for user interfaces or error messages was highlighted by Participant 5 as particularly valuable, likely due to AI's strength in language-based tasks. Multiple participants (3 and 4) emphasized the drafting of PRDs and documentation as high-value applications. Participant 4 specifically valued AI's ability to summarize meeting notes or developer feedback. Participant 2 appreciated how AI could break down complex problems into manageable components. These high-value applications typically focus on structured communication and information processing tasks.

Conversely, participants identified several areas where AI consistently fell short of their expectations. All participants expressed skepticism about AI's capabilities for innovative or creative thinking, with several explicitly noting its limitations. Participant 5 found AI particularly disappointing for competitor analysis and market trends research, citing a lack of depth and current information. Participant 3 highlighted poor data analysis and forecasting performance, where accuracy and context awareness are critical. Most strikingly, all participants unanimously agreed that AI failed to deliver radical innovation, suggesting fundamental limitations in AI's ability to transcend existing patterns and generate novel ideas.

4.2.1 Productivity and efficiency gains

Despite varying assessments of their overall impact, the acceleration and efficiency benefits of GenAI tools were consistently highlighted. Participant 1 acknowledged that AI significantly speeds up their work, claiming they "wouldn't be able to work this fast without it." Participant 2 provided more specific metrics, noting that tasks typically take three days to complete and could be finished in half a day with GenAI assistance. Participant 3 emphasized time savings in research and documentation activities, estimating that "an action that would normally take 40 hours can now be completed in 4-5 hours" using AI. Participant 4 estimated nearly a tenfold increase in efficiency when using GenAI to draft documents compared to creating them from scratch.

Participant 5 offered a more nuanced perspective, suggesting that while GenAI might improve output quality, it also increases the total time spent on tasks, potentially nullifying the net efficiency gains: "It might improve the quality of work, but it also increases the time I spend on a task. Maybe these balance each other out." Participant 9 strongly emphasized productivity benefits: "It dramatically increases efficiency. You can accomplish much more in less time, access more information quickly, and prepare documents faster. You genuinely get much more done in much less time."

4.2.2 Adoption motivations

Productivity enhancement emerged as a primary driver for AI adoption among several participants. Participant 1 explicitly identified "time management" as their primary motivation for incorporating AI into their workflow. Similarly, Participant 4 stated that "my only motivation has been time-saving," suggesting a pragmatic approach focused on efficiency gains. Participant 9 emphasized this perspective: "The most important advantage is that instead of searching for something in a search engine, it gives you the answer directly. And what does this give me? Time." These participants appear to have integrated AI specifically to address workflow optimization needs.

In contrast, other participants described more exploratory motivations driven by curiosity and technological interest. Participant 3 began using AI "to keep up with technological developments," suggesting a desire to remain current with industry trends. Participant 5 provided the most detailed account of exploratory adoption: "I started using it because of the hype - I wanted to discover what it could do, not for a specific need." This participant also noted being influenced by social media trends: "Social media trends influence me - I try prompts I see on TikTok or Instagram."

Participant 6 described his adoption as inevitable given the technological environment: "Since we're deeply involved in technology, our tendency to catch trends, notice them, and figure out how to incorporate them into our system was essentially unavoidable for us. That's why... I feel like we had to use it."

These contrasting adoption motivations suggest that while some product managers approach AI with specific productivity goals, others integrate it through experimentation and discovery.

4.3 Focus Area 2: Unintended Consequences: Emerging Themes

The product managers interviewed for this study revealed several unexpected consequences of integrating GenAI into their ideation processes. Despite initially adopting these tools to enhance productivity, participants described a complex range of unforeseen effects on their creative processes, team dynamics, and decision-making habits. Participant 5 candidly observed, "I initially thought it helped my creative process, but now I find myself going straight to AI without thinking first," highlighting how tools adopted for efficiency sometimes reshape cognitive habits in unanticipated ways. Participant 3 expressed concern that GenAI would "make product managers lazy" over time. Participant 1 noted that using AI outputs without critical thinking can lead people to become lazy.

Participant 7 also reflected on unexpected dependency concerns: "I'm quite obsessed with these topics... I'm particularly fixated on the brain's development. I try not to rely too heavily on AI for this reason." Participant 8 expressed similar worries about mental capabilities: "I worry about dependency issues. Having a personal assistant constantly at your side is very comfortable, but what if we ever lost access to it? That's concerning." Participant 9 noticed behavioral changes: "I've become somewhat dependent on it. I must consult it even when I know the answer, thinking it might suggest something better."

Participant 6 observed how AI occasionally confused contexts across conversations: "When I've talked to it about my eye surgery, then later asked about a dream I had, it interpreted the dream as reflecting anxieties about the eye surgery." This context contamination was noted by other participants as well, with Participant 7 describing: "I see repetition patterns, especially when it connects previous conversations. For example, I might have talked about an application problem and a mobile problem. However, when I want to discuss the web product, it still gives me mobile-related references."

The interviews revealed that experienced product managers have started developing informal practices to mitigate these unintended effects. For instance, Participant 3 described thinking independently before consulting AI "to avoid bias." Participant 4 revealed an unwritten company rule prohibiting the mention of their employer to AI tools due to concerns about data security. Participant 7 explained their adaptation strategy: "I try not to ask about things I haven't thought through myself. I'm reluctant because I don't want my brain muscles to atrophy."

Multiple participants expressed reluctance to use AI for high-stakes creative or strategic decisions. Participant 5 stated they would "never go to business stakeholders with AI-generated content without significant editing." Participant 8 described developing more selective usage patterns: "I sometimes use incognito mode to talk to it. I don't want it to learn and connect my accounts." Participant 9 similarly developed personal safeguards: "Sometimes I close the session and open a new one when looking at sensitive information. It might seem silly, but I don't want to use that information for my model."

These emerging adaptations suggest product managers are actively negotiating the boundaries of appropriate AI use through practical experience rather than formal guidelines, as all participants noted their organizations lacked formal policies for GenAI usage. Participant 6 noted, "I don't think our company has any guidelines; if they do, nobody knows about them. Probably they don't exist." This lack of formal guidance has led to the organic development of personal risk management strategies across the product management community.

4.3.1 GenAI-induced creativity fixation

The most prevalent unintended consequence mentioned across interviews was AI's potential to constrain rather than enhance creative thinking. Ten participants expressed concerns that their creativity was being negatively affected by regular AI use. Participant 1 articulated this most directly, stating that AI "suppresses and prevents human creativity" and observed that "people can become lazy by directly using the output without thinking further." This concern about cognitive laziness was echoed by Participant 3, who predicted that "AI will reduce human creativity in the long term" and "will make product managers lazy," adding that since AI primarily looks to past data, human creativity becomes inherently constrained.

Participant 5 provided valuable insights into the evolving relationship with AI-assisted creativity, noting: "I initially thought it helped my creative process, but now I find myself going straight to AI without thinking first, which has reduced my creativity." This participant elaborated on this cognitive shift, admitting: "I feel like it's making me dumber because I now instinctively want to ask AI before thinking for myself." The chronological progression described by Participant 5, from initial creative enhancement to eventual creative dependency, suggests a concerning trajectory of diminished creative capabilities through habitual AI reliance.

Participant 7 shared similar concerns: "I'm somewhat obsessive about these topics... I avoid asking about things I haven't thought of myself unless it's writing a document or creating a file. I will stay away from it." Participant 8 stated: "I'm quite meticulous about not overusing it... I try not to rely on calculators much, either. I prefer to multiply numbers mentally. I exercise my brain that way... just like with physical exercise, the brain muscles work the same way."

However, this negative assessment was not universal. Participant 2 offered a contrasting perspective, asserting that AI "doesn't limit creativity" and "allows more time for creativity and accelerates the creative process." This participant suggested that rather than replacing creative thinking, AI might augment it, noting that "AI's suggestions can trigger different ideas, helping discover new perspectives." Participant 9 similarly believed that GenAI does not limit creativity: "I don't think it limits creativity. Yes, it doesn't say anything new beyond what I've thought of... but I don't think that means it limits creativity. On the contrary, I think it's beneficial."

This divergence in experiences suggests that AI's impact on creativity may depend significantly on individual usage patterns and conscious integration strategies, with some individuals experiencing an enhancement of their creative capabilities while others experience atrophy.

There was notable consensus around AI's limited creative capabilities, particularly for innovative ideation. Participant 1 stated that they don't use AI for creativity because they don't find it creative, noting it produces "basic and standard things." Similarly, Participant 4 found that AI cannot go "a step further" in areas where human creativity is struggling. Most participants framed AI as better suited for augmenting existing ideas rather than generating novel ones, suggesting a pattern in which AI may reinforce existing thinking patterns rather than expanding creative boundaries.

Various forms of dependency on AI tools were reported across participants, though with differing levels of concern. Participant 1 identified dependency as "an issue, especially with freely available tools," suggesting widespread accessibility may accelerate dependency formation. Participant 5 provided the most candid self-assessment of dependency development, acknowledging: "I've become somewhat dependent on it. I must consult it even when I know the answer, thinking it might suggest something better." This compulsive checking behavior suggests the development of cognitive dependencies that extend beyond mere practical utility, raising questions about the long-term impact on professional capabilities.

Other participants described more managed relationships with AI tools. Participant 2 asserted that "team members becoming dependent is not currently an issue for product managers," expressing the view that "dependency doesn't produce value. Becoming dependent on creating standard things isn't beneficial." This participant emphasized viewing GenAI as an "accelerator" rather than a replacement. Participant 3 maintained boundaries by using "AI as an input mechanism but evaluating results using my own experience, so I'm not at a dependency level." Similarly, Participant 4 emphasized that "in my process, there isn't much dependency because we still need the human factor to create and implement solutions."

Participant 8 described an interesting behavior pattern reflecting dependency concerns: "I'm concerned about dependency issues... having something that acts like a personal assistant constantly by your side is quite comfortable. But if we were to live in a world where we no longer had access to this... I think that's concerning."

Participant 9 reflected on potential dependency risks more directly: "I'm worried about dependency... Having this personal assistant-like thing constantly with you is very comfortable. But if there's a future world where we don't have access to this... It's worrying, I think. Concerning."

These perspectives suggest that product managers are developing different levels of awareness and strategies regarding dependency risks, with some actively maintaining cognitive independence while leveraging the capabilities of AI.

An interesting pattern emerged regarding the progression of dependency over time. Multiple participants noted that their AI usage evolved from occasional assistance to regular consultation, even for tasks they had previously handled independently. This argument suggests that dependency may develop gradually and subtly, even among professionals conscious of the risks.

Participants described various intentional limitation strategies to preserve creative autonomy while benefiting from AI assistance. Participant 3 emphasized thinking about ideas independently before consulting AI "to avoid bias," preserving original thought processes. Participant 5 developed domain-specific limitations, noting that "for creative tasks, I prefer researching on Google or reading Medium articles instead of relying on AI," effectively reserving certain creative activities for human-only thinking.

Several participants described complementary usage approaches that position AI as an enhancer rather than a replacement for human creativity. Participant 4 explained: "I use it to organize my thoughts and see where I'm going with ideas, not to generate the ideas themselves," maintaining primary creative ownership while using AI for refinement. Participant 5 developed a staged approach: "I find articles or sources first, then ask AI to help me interpret them concerning my problem, rather than asking it to solve from scratch."

Participant 7 explicitly worked to counteract potential dependency: "I try to think about something first before asking about it... I don't expect too much creativity from it, and I don't ask for it either." Participant 8 adopted a balanced approach: "I'm somewhat strict about it because I care about mental regression... I generally try to avoid asking about things I haven't thought about unless it's writing a document or creating a file."

These adaptation strategies suggest that product managers actively develop methods to harness AI's benefits while protecting their creative capabilities and avoiding over-reliance.

A notable aspect of these adaptation strategies is their evolution as participants gained experience with AI's limitations. Several participants mentioned modifying their initial approach after experiencing disappointing creative outputs, suggesting an iterative learning process in developing effective human-AI collaborative workflows. This issue highlights the importance of organizational learning and knowledge sharing about effective AI integration practices.

4.3.2 Standardization of innovation

A striking pattern emerged across all interviews: GenAI tends to produce standardized, predictable outputs rather than truly innovative ideas. This uniformity in AI-generated content represents a significant concern for product managers whose competitive advantage often depends on differentiated thinking. Participant 3 bluntly stated, "It's not innovative," explaining that AI typically presents "things that have been known in the market for a long time, compiled and collected." This sentiment was echoed by Participant 1, who, after several attempts with GenAI for ideation, found it only capable of producing basic and standard things.

Participant 6 reinforced this observation: "I think it's not good at providing new ideas or being creative right now. No matter how well you define its needs and problems, it usually just lists the first three options that would come to anyone's mind." Participant 7 attributed this limitation to AI's training methodology: "Since Generative AI feeds itself from surrounding information and data, it isn't capable of producing truly innovative things. Honestly, I don't expect or anticipate that it would." Participant 8 noted the lack of creative breakthroughs: "I haven't had any 'wow' moments. It repeats itself or says the same things with different sentences."

Participant 9 provided a concrete example of this standardization: "We're trying to figure out how products should be ordered in the category listing screen in our app. I asked what parameters I should consider when ordering products. While it gave me parameters, they were very generic things I already knew. Nothing that made me think, 'Oh, I hadn't considered that.'" This recurring pattern of receiving obvious, standard responses rather than novel approaches frustrated participants hoping for breakthrough thinking.

The interviews revealed a consensus on AI's limitations in capturing current industry trends and breakthrough thinking. Participant 5 characterized AI's outputs as "outdated thoughts" that fail to capture current trends, noting that the responses lacked contemporary relevance even when asking about promotion trends. Similarly, Participant 2 observed that AI "doesn't contain radical innovation and doesn't propose contradictory ideas," instead staying in line with what currently exists. Participant 4 shared a frustrating experience where, despite repeatedly clarifying they were asking about mobile app accessibility, the AI persistently provided web-focused answers, demonstrating an inability to adapt to specific contextual requirements.

Participant 8 elaborated on this limitation: "I don't think it follows industry trends. It goes back to basics, providing foundational information that's learned." Participant 6 noted that AI responses lack situational awareness: "I asked about brand creation and messaging, and it just gave me generic marketing concepts rather than anything tailored to our market context." These experiences highlight how AI systems typically regurgitate established knowledge rather than incorporating cutting-edge trends or domain-specific innovations.

This standardization manifests not only in the content of ideas but also in their expression. Participant 5 noted that AI has a language style that can't deviate from, even when attempting to generate content for different user personas. Participant 3 argued that when repeatedly querying AI on the same topic, "again, 90-95% the same things, just written in different sentences." Even more concerning, Participant 1 discovered that "when using two different GenAI tools, the results were very similar," suggesting this standardization extends across different AI systems, potentially leading to industry-wide homogenization of product ideas if widely adopted without critical intervention. This participant concluded that AI "is not creative because it presents what comes to mind most readily," suggesting outputs are biased toward common or conventional ideas.

Participant 6 observed this content homogenization directly when interviewing candidates who used AI for their application materials: "Their mockups were remarkably similar," indicating that AI produced standardized design approaches across different users. Participant 7 noted that this standardization might extend beyond just content: "Since it probably suggests the same technical structure to everyone when asked about the same problem, it's likely creating technical standardization too, not just in innovation."

Beyond general standardization, participants noted that AI struggles with domain-specific understanding. Participant 3 observed that AI "can't produce ideas tailored to a specific product's pattern because it doesn't know the context," highlighting limitations in contextual adaptation. Participant 4 described a frustrating example where "when I asked about mobile app accessibility, it kept giving me web-focused answers despite repeatedly clarifying I was asking about mobile," demonstrating difficulty maintaining context-specific focus. Participant 5 found AI's responses disappointingly generic, noting, "It provides very generic answers that I could find on Google." The participant explained that while benchmarking, the AI would provide only limited examples from obvious competitors, rather than drawing inspiration from diverse industries or innovative approaches.

Participant 8 elaborated on this lack of specificity: "When I ask about e-commerce promotion strategies, it gives surface-level answers without depth or context. It feels like combining known elements rather than creating something truly insightful." Participant 9 described a ready basket feature they were developing: "I asked what factors I should consider when creating ready baskets for users, but it just gave generic answers like 'look at her toilet paper purchasing patterns' or 'what times she uses the app' – things I already knew."

These experiences suggest that AI systems lack the deep domain understanding and creative connecting abilities to generate relevant and specific innovation ideas. The standardization effect stems from multiple factors: AI's training on historical data rather than emerging trends, its tendency to average across established patterns rather than explore boundaries, and its limited ability to incorporate specific contextual factors that might drive truly differentiated innovation. For product managers seeking competitive advantage through creative differentiation, this standardization represents a significant limitation that requires deliberate mitigation strategies.

A unanimous consensus emerged regarding AI's inability to generate radical innovation. None of the participants found AI capable of producing truly novel ideas that significantly departed from existing approaches. Participant 3 noted that AI "offers simple solutions that anyone could think of," suggesting a lack of sophisticated, innovative thinking. Participant 1 observed that AI "can only modify what exists rather than create truly new ideas," highlighting its incremental rather than transformative approach. Participant 2 found that AI generally "stays in line with existing approaches" rather than challenging conventions. Participant 3 described attempting to push AI toward creative thinking but found that "when I ask for creative solutions, it gets stuck in a pattern and produces similar variations." Participant 5 was the most direct, stating, "I haven't found it innovative at all," and emphasized that AI consistently provided outdated and predictable ideas. Participant 1 explicitly mentioned that they don't use AI for ideation because they don't trust it, having tried it several times without achieving "very different, productive results."

Participant 6 similarly reported: "I think it's not good at providing new ideas or being creative right now. No matter how well you define its needs and problems, it usually lists the first three options that would come to anyone's mind." Participant 7 explained: "Since Generative AI feeds itself from surrounding information, it doesn't provide truly innovative things. I'm honestly not expecting it to, and I don't anticipate it would." Participant 9 shared the same observation: "I haven't encountered creative ideas... It repeats itself or says the same things in different sentences." This consistent assessment across all participants suggests a fundamental limitation in current AI systems' capacity for breakthrough thinking.

Participants also identified significant limitations in the analytical depth of AI. Participant 5 found that "the analysis lacks depth when benchmarking competitors" and "when I ask for promotion trends in e-commerce, it gives very surface-level answers without depth or context." This participant provided a specific example where AI's analysis of feature performance data felt utterly disconnected from the context, noting it seemed "like another PM's analysis" rather than a meaningful interpretation of the specific data provided. Similarly, Participant 4 noted that AI "doesn't provide the level of detail I need for meaningful competitive analysis." Participant 3 reported that in numerical analysis, such as pricing tables and forecasting, AI made errors that required time-consuming verification, making it inefficient for these tasks. These observations suggest AI currently excels at breadth of information but struggles with providing the depth required for truly insightful innovation work, often producing analyses that feel generic and disconnected from specific contextual requirements.

To overcome the standardization tendencies of AI, participants developed various augmentation approaches. Participant 2 suggested that "taking the GenAI output further prevents standardization" and recommended "adapting outputs to specific needs by building upon them." Participant 3 described a filtering process where they "filter out illogical ideas and shape logical ones to be more applicable." Participant 4 emphasized that they "never use AI output directly; I always need to adapt it to our specific context and constraints." Participant 5 similarly stated, "I would never go to business stakeholders with AI-generated content without significant editing," and described how they needed to provide extensive context and their frameworks to get useful outputs, noting, "I created a matrix and gave it to AI" when working on a mobile highlight module task.

Participant 6 explained a similar approach: "I don't use the outputs directly. I always take what I get and build on it... We're business idea developers. We transform products. Then, we go back and continue to adapt them to our needs. It's like seeing all the possibilities and choosing from them, then we keep going on our own." Participant 7 described thinking independently before consulting AI: "I try to think of some ideas myself before asking, without assistance... After comparing what I've thought of with what comes back, a concept forms in my mind."

These approaches position human judgment as essential for transforming standardized AI outputs into unique, context-appropriate solutions.

Some participants also implemented strategic use limitations, consciously avoiding the use of AI for specific tasks. Participant 1 stated that they "don't use it for creative tasks where differentiation matters," thereby preserving human creativity for areas that require originality and innovation. Similarly, Participant 4 noted, "For strategic matters, I don't rely on AI as much because I don't trust its judgment," maintaining human oversight for critical decisions. Participant 5 described shifting away from using AI for creative tasks after finding its outputs consistently disappointing; instead, they preferred to research on Google or read Medium articles for creative inspiration. These selective usage patterns suggest product managers are developing nuanced approaches to AI integration, leveraging its strengths while compensating for its limitations through strategic task allocation.

Several participants noted that AI might be more useful for junior product managers who need basic guidance. In contrast, experienced managers find standardized outputs less valuable. Participant 1 mentioned explicitly that AI might be useful for junior PMs but insufficient for those with foundational knowledge. This account suggests a potential role for AI in professional development pathways, with utilization potentially evolving as expertise increases.

4.3.3 Decision-making bias and automation reliance

The interviews revealed significant concerns about how GenAI influences decision-making processes and creates new dependencies in product management workflows. A recurring theme was the challenge of verifying AI-generated information and the resulting impact on critical evaluation. As Participant 4 explained, "I try to get references when AI answers so that I can cross-check," but often encountered difficulties because "AI often can't provide proper citations." This verification challenge created a troubling epistemic situation where the same participant admitted, "Sometimes I have to use it as a source even when I can't verify the information," potentially propagating unverified information through decision chains.

Participant 8 described a similar verification dilemma: "When evaluating AI-generated content, I always filter it through my judgment. But sometimes, if it's something I don't know much about. If I'm not an expert in that domain, I become dependent on it. Sometimes, I can't even cross-check it with Google searches." Participant 7 mentioned being particularly cautious with technical information: "When it suddenly turns technical and gives line-by-line code or suggests datasets to create, I sometimes find it difficult to evaluate that content. I've ignored its suggestions in these cases, treating them as if they weren't given."

Assessment of output quality presented additional challenges for participants. Participant 4 described a trust hierarchy based on verifiability: "If I can't cross-check or find references, my trust is very low because it might be making things up." The same participant noted organizational skepticism, stating, "When I mention ChatGPT as a source in team discussions, there's often pushback and requests for additional research." Interestingly, AI-generated content appears to carry identifiable characteristics that trigger scrutiny. Participant 4 observed that "there's a tendency to reject content that lacks the human touch, as people can recognize AI-generated content."

Participant 5 described having a critical approach to AI outputs, noting they rarely trust AI's suggestions without verification, especially for important business decisions: "I don't trust what it does and says. If it's going to be for something critical, especially if I'm going to use it for my work and not present it to someone, I don't pursue it further." Participant 9 shared a similar sentiment: "I don't check every word it writes, but I review everything through my filter. If I'm asking it to calculate something, I cross-check those calculations." These dynamics suggest the emergence of socio-organizational mechanisms for evaluating and sometimes discounting AI-generated contributions to decision-making processes, with individuals and teams developing increasing skepticism toward unverified AI outputs.

Trust issues emerged prominently across interviews, with participants developing nuanced hierarchies of when to rely on AI outputs. Participant 5 shared a concerning experience that undermined their confidence: "It gave me wrong information about astrology, then immediately admitted its mistake," which made them wonder, "What kind of errors is it making that I'm not noticing?" Similarly, Participant 3 found that AI made errors in numerical analyses, such as pricing tables and forecasting, which required time-consuming verification. Participant 8 highlighted basic factual errors: "Sometimes it provides incorrect data. You could find the correct answer with a simple Google search, but it gives seriously erroneous data." Participant 9 mentioned calculation issues: "I was shocked about its calculation problems. How can it not calculate the difference between two hours?"

Participant 6 described a trust calibration process: "I generally place trust in its output up to a point because it has access to so much information that it must know something. There's so much source material that there must be a trend in those sources." However, this participant acknowledged limitations: "I never use it for anything that could put me in a difficult situation."

The influence of GenAI on team dynamics and organizational decision-making revealed interesting patterns. Participant 4 observed that "when I mention ChatGPT as a source in team discussions, there's often pushback and requests for additional research," indicating organizational skepticism toward AI-sourced information. Participant 5 found that when presenting AI-generated naming suggestions to senior management and the legal team, they were met with skepticism and concerns about potential trademark infringement. The participant elaborated: "The legal team and upper management didn't find these suggestions very good, and they didn't pass the approval process." Participant 9 mentioned that AI positively influenced decision-making: "It positively affects my decision-making processes. I want to consider the pros and cons when making a decision; sometimes, I'm too lazy to do this myself. With AI, it's very easy; it lists the ideas, creates a table, and makes everything much clearer." Participant 2 observed improved collaboration when team members shared a common understanding of AI tools, noting that this created a shared foundation for discussing and building upon ideas.

Product managers described developing context-dependent automation strategies, deliberately limiting the use of AI in specific domains. Participant 4 noted they primarily use AI for "routine tasks like drafting documentation," while maintaining that "for strategic decisions or creative direction, human judgment remains primary." Participant 3 characterized their approach as using AI like "an input machine," emphasizing that "at the end of the day, I don't use the results 100%. I evaluate them using my own experience, too." Participant 7 similarly described: "I never used AI for ideation directly. I've always had something in mind, a problem with a certain solution, and discussed how we could approach it."

Participant 2 attempted to use AI for retrospective meeting facilitation but found it less successful than human discussion. Participant 6 noted domain-specific limitations: "I don't use it for visual understanding. It struggles with that. I once tried to have it draw mock-ups or wireframes, but it created horrific results." Participant 9 established clear boundaries: "I do additional work on AI outputs. I've never had a situation where I thought, 'This is so good I can use it directly." These emerging patterns indicate that product managers are actively developing judgments about when automation is beneficial versus when human oversight remains essential, often learning through trial and error rather than relying on formal guidance.

The interviews revealed an evolving relationship with AI in decision-making contexts, characterized by cautious integration, skeptical assessment, and domain-specific application rather than wholesale adoption. Product managers appear to be developing sophisticated mental models for when and how to incorporate AI inputs into their decision processes, treating AI as one stakeholder voice among many rather than as an authoritative source.

AI tools appeared to influence team dynamics in several notable ways. Participant 5 found that AI "can help bridge communication gaps between technical and non-technical team members," serving as a translator between specialized domains. The same participant noted that "in difficult conversations with stakeholders, AI suggestions have helped navigate conflicts successfully," suggesting applications in conflict resolution and stakeholder management. Collaborative creation processes also emerged, with Participant 5 observing that "using AI can facilitate collaboration between UX writers and product managers," creating shared creative workflows. This participant described a specific collaborative process where they and a UX writer would independently ask AI similar questions with different prompts, then compare the results and select the best elements from each response.

Participant 7 noted team collaboration benefits: "I think it supports collaboration the most between PMs. When working with my product manager colleague, we use it a lot. For example, he creates an AI output. I create something, we send it to each other, and we share its outputs. In this way, I think it supports collaboration."

These experiences suggest that AI is becoming integrated into team communication patterns, extending beyond individual productivity to create new collaborative workflows.

Perceptions of authority appeared to be influenced by AI attribution in team settings. Participant 4 observed that "when referencing AI in team discussions, there's often skepticism if no additional sources are provided," suggesting reduced credibility for explicitly AI-sourced information. The same participant noted that "team members can recognize AI-generated content and may discount it for lacking human insight," indicating the persistence of human authority in evaluating information quality. Participant 5 described how suggestions for naming product categories from AI were met with skepticism from senior management and the legal team, who found the suggestions less compelling and potentially problematic from a legal standpoint. In contrast, Participant 2 found positive team effects, noting that when sharing AI-generated ideas with a junior PM, the junior could build upon them. Team members familiar with AI tools could collaborate more effectively. These divergent experiences suggest that organizational contexts have a significant influence on how AI-generated content is received and valued in collaborative settings.

Participants described context-dependent reliance patterns that varied by task type. Participant 4 noted that "higher reliance is acceptable for routine tasks like drafting documentation," suggesting comfort with automation for structured, lower-risk activities. However, multiple participants maintained that "for strategic decisions or creative direction, human judgment remains primary," preserving human authority for high-consequence choices. Participant 5 was particularly cautious about stakeholder-facing content, stating, "I wouldn't go to business stakeholders with AI-generated content without significant editing," suggesting sensitivity to reputational risks. The same participant explicitly noted avoiding AI for creative tasks and strategic decision-making, preferring to rely on human judgment and traditional research methods in these areas.

Participant 2 specifically mentioned limited success using AI for retrospective meetings, where human discussion seemed more effective. Participant 8 described a clear task-based hierarchy: "I will use AI to organize information and prepare documents, but for strategic matters, I rarely rely on it because I don't trust its judgment." Participant 9 similarly differentiated: "I use it extensively for Jira tasks and documentation, but for creative thinking or important business decisions, I always apply my filter." These differentiated approaches suggest that product managers are developing nuanced heuristics for determining appropriate automation levels across various task domains, with routine, structured tasks being deemed more suitable for AI assistance than creative or strategic activities.

Complementary integration approaches emerged as strategies for balancing AI and human contributions. Participant 4 described a sequential process where "I use it to gather information but apply my critical thinking to the final decision," maintaining human authority while leveraging AI efficiency. Participant 5 outlined a collaborative filtering approach with team members: "With UX writers, we use AI suggestions as options to select from rather than final solutions," positioning AI as an idea generator rather than a decision-maker. The same participant expressed a preference for finding information through traditional means and using AI to help interpret or apply that information to their specific context, rather than relying solely on AI as the primary source of information.

Participant 3 appreciated using AI as an "input machine," emphasizing that they never relied on the results at 100% but instead evaluated them in conjunction with their own experience. Participant 6 described a dialogue-based approach: "I treat it as a conversation rather than accepting what comes directly. I have an idea and ask, 'What do you think?' expecting it to contribute perspectives and enhance what I already have." Participant 7 maintained creative primacy: "I never ask for completely new ideas. I always have something in mind, a problem with a certain solution, and we discuss how we might implement it." These integration patterns suggest the emergence of human-AI workflows that preserve human judgment while amplifying capabilities through AI assistance, with humans generally maintaining final decision authority while leveraging AI for idea generation, option expansion, and efficiency enhancement.

This emerging pattern of human-AI complementarity reveals a sophisticated adaptation among product managers, where AI is positioned as an advisor, amplifier, or accelerator rather than an autonomous decision-maker. These professionals appear to be intuitively developing what might be called "AI literacy," the ability to discern where AI inputs add the most value and where human judgment remains essential. Importantly, this literacy involves a technical understanding of AI capabilities and metacognitive awareness of one's decision processes. The participants' experiences suggest that effective AI integration requires maintaining a balance between complete reliance and independence, preserving space for human creativity, critical thinking, and contextual judgment while leveraging AI for its strengths in information processing and pattern recognition. This balanced approach allows product managers to enhance their capabilities without surrendering their professional judgment or creative agency.

4.3.4 Ethical and IP concerns

The interviews uncovered significant ethical and intellectual property concerns that product managers face when integrating GenAI into ideation processes. Data security emerged as a primary concern, with participants developing informal safeguards against potential information leakage. Participant 4 revealed an unwritten organizational rule: "I have an unwritten rule not to mention my company name to AI tools," and expressed personal concerns about identity disclosure, noting, "I worry that mentioning my role at the company could somehow link my conversations to the company." This caution extended to proprietary information. Participant 5 highlighted a fundamental tension: "To benefit from AI fully, I would need to upload meeting notes and documentation, which raises privacy concerns." These perspectives suggest that product managers must balance the need for AI functionality with the requirement for organizational data protection.

Training data concerns also appeared in participant responses. Participant 1 mentioned that "the data used to train AI poses a risk in terms of data security," suggesting awareness of potential upstream vulnerabilities in AI development processes. Participant 5 expressed concerns about data exposure when brainstorming new product features or strategies with AI, worried that competitors or those with access to proprietary business information could potentially use the information. Participant 9 shared a specific privacy concern when AI referenced personal information: "I got very concerned when it mentioned someone's name from my life. I wondered if I had previously mentioned this name somewhere."

Intellectual property considerations revealed divergent viewpoints among participants. Participant 1 articulated significant concerns, stating that "ideas produced by AI belong to the AI itself" and warning that "the same idea could be given to different people, including competitors," which could potentially undermine a competitive advantage. In contrast, Participant 2 offered a more relaxed assessment, asserting "GenAI isn't risky in terms of intellectual property rights" and drawing comparisons to open-source innovation models, noting that "similar to open-source communities, building upon ideas creates differentiation." This philosophical divide suggests that the industry is still developing a consensus on the appropriate IP frameworks for AI-assisted innovation.

Practical IP challenges emerged in specific use cases. Participant 5 described an incident where AI suggested product category names already used by competitors, including potentially trademarked phrases like "select-choose-take." This participant noted that their legal team found these suggestions potentially problematic and required legal verification before implementation. Similarly, Participant 3 mentioned considering AI integration for banner creation but recognized potential ethical and IP risks that would necessitate human oversight of outputs. These examples demonstrate how seemingly straightforward applications can create unexpected legal exposure.

The interviews highlighted concerns about AI-generated misinformation affecting business decisions. Participant 4 worried about scenarios where "if I use unverified AI information saying 'this approach increased conversion by 45%', I could be misleading my developers or managers." Participant 5's experience with AI confidently providing incorrect information about astrology, only to immediately acknowledge the error when challenged, significantly undermined their trust in other outputs. These instances highlight fundamental epistemic challenges associated with incorporating AI-generated information into decision-making processes.

This awareness of AI system architecture and data flow suggests that product managers are developing a more nuanced understanding of AI's comprehensive data lifecycle and its associated security implications. This argument leads to cautious approaches to information sharing with AI systems.

Participants expressed diverse views on the intellectual property risks associated with AI. Participant 1 raised concerns about idea ownership, stating that "ideas produced by AI belong to the AI itself" and warning that "the same idea could be given to different people, including competitors," which could lead to potential competitive disadvantages. This participant considered AI ethically risky in this regard. In contrast, Participant 2 offered a more relaxed assessment, asserting "GenAI isn't risky in terms of intellectual property rights" and drawing parallels to open innovation models, noting that "similar to open-source communities, building upon ideas creates differentiation." This participant noted that product copying is widespread, suggesting that further development of AI outputs can create sufficient differentiation to mitigate IP concerns.

Participant 5 provided specific examples of intellectual property concerns, describing how, when using AI to help generate names for product categories, it suggested terminology already used by competitors, including potentially trademarked phrases like "select-choose-take from a competitor." The participant noted that the legal team found these suggestions problematic and required legal verification before they could be implemented. This experience highlighted how AI may inadvertently suggest protected intellectual property without proper attribution or clearance, thereby creating legal risks for organizations that implement these suggestions without proper vetting and due diligence. Participant 3 mentioned considering AI integration for banner creation but recognized the potential ethical and IP risks, which require human oversight of the outputs. These contrasting perspectives and experiences suggest product managers are still developing consensus around appropriate intellectual property frameworks for AI-assisted innovation, with some taking a more cautious approach. In contrast, others see parallels to existing open innovation models.

Multiple participants highlighted factual accuracy concerns. Participant 4 noted that "AI can make up statistics or case studies that sound plausible but are not verified," pointing to fabrication risks. This participant described potential consequential scenarios, such as, "If I use unverified AI information saying 'this approach increased conversion by 45%', I could be misleading my developers or managers." Participant 5 shared a personal experience that undermined trust: "I caught it making a mistake about my astrological chart, which made me question what other errors it might be making that I'm not catching." This participant noted that the AI confidently provided incorrect information and immediately acknowledged the error when challenged, which significantly damaged trust in other outputs. The concern about undetected errors in domains where participants lacked the expertise to verify them emerged as particularly troubling, suggesting a fundamental epistemic challenge in AI-assisted decision-making.

Participant 8 described encountering inaccuracies: "Sometimes it provides very obviously incorrect data. Even if you searched Google, you would find the correct information. It gives seriously erroneous data... it was so obvious, like saying two plus two equals five." Participant 9 noted calculation errors: "I was shocked about the calculation issue. How can it not calculate the difference between two hours?" These experiences with basic factual errors contributed to the participants' cautious approach to AI outputs.

Despite these concerns, oversight and governance mechanisms remained largely informal. None of the participants reported formal company guidelines for AI use. Participant 4 noted, "The company doesn't have guidelines, but we use our judgment about what information to share." Participant 5 explicitly mentioned that, although no formal guidelines existed, having such guidance would be welcome to provide more precise parameters for appropriate use. Participant 3 mentioned checking the legal compliance of AI-generated ideas before implementation in the absence of formal review processes. This gap between emerging risks and formal governance structures suggests organizations are still in the early stages of developing comprehensive approaches to managing AI's potential downsides in product management contexts, leaving individual product managers to develop risk management practices based on personal judgment and informal norms.

4.4 Focus Area 3: Future Outlook and Recommendations

4.4.1 Evolving role of AI in product management

All participants believed that the role of AI in product management would continue to increase in the future. However, they differed in their assessment of its ultimate impact on the profession. Participant 3 predicted that "this trend will increase... it's not completely a bubble. And it's already changed our lives." Participant 8 said, "I think it will increase tremendously in the long term. It's already increased now. Specific people are using it much more effectively... At some point, everyone will be powerful in AI."

Participant 7 expected that "in the long term, it will increase massively. Currently, it has already increased significantly... At some point, there will be a breaking point for certain things... just like how we started using the internet." Participant 9 expressed similar confidence: "In the long term, it will increase as long as it continues to be developed."

Despite this consensus on the increasing use of AI, participants agreed that AI would not completely replace product managers. Participant 3 explained: "Product managers will be more supportive in this role, but it might make juniors more uncomfortable. I think that's how it will be." Participant 7 emphasized: "I don't think it will eliminate any job, especially product management... because AI still struggles to understand people's emotions, feelings, and psychology... I think product managers' roles will increase rather than decrease."

Participant 8 predicted a transformation rather than eliminating the role: "In 10-15 years, product management could be very different. It might seem like a completely different profession... Looking at it then, teleporting there, we might say, 'Wait, what are they doing?' It could be that kind of situation."

Participants envisioned a future where AI handles more routine, systematic tasks, freeing product managers to focus on more strategic, empathetic, and creative aspects of their work. Participant 7 described this evolution: "I think we'll become more self-sufficient. Currently, there are people around us who can do things we cannot do, from taking a product from start to finish; it's a team effort. But AI will gradually take over those team efforts' more automated, technical parts."

Participant 8 expected significant automation of routine tasks: "A huge part of our work could be handled with AI... Documentation, perhaps prioritization, roadmaps, and features that could improve existing products, AI could generate most of these. It could measure them, take automatic actions based on measurements."

Several participants predicted that while AI might reduce the need for specific technical skills, it would increase the importance of human judgment, strategic thinking, and stakeholder management. Participant 3 noted that "soft skills, persuasion abilities, presentation capabilities" would remain difficult for AI to replicate.

4.4.2 Recommendations for AI integration

When asked what advice they would give to other product managers considering GenAI use, participants offered several consistent recommendations:

Start using it immediately: Multiple participants emphasized the importance of integrating AI into workflows as soon as possible. Participant 7 advised: "They should start using it immediately. I don't think it's enough to use it as it is. I feel like I'm falling behind." Participant 3 suggested: "Definitely use it; don't hesitate to try it. You can save time and make your work easier in areas that will help you."

Maintain critical thinking: Many participants stressed the importance of using AI as a complementary tool rather than surrendering decision-making to it. Participant 3 advised: "But of course, don't trust everything 100% and use it directly. To avoid killing creativity, I think about things myself first." Participant 8 warned: "Use it as a tool... don't rely on AI completely."

Focus on value-adding activities: Several participants recommended utilizing AI to automate routine tasks, enabling product managers to concentrate on more creative and strategic work. Participant 9 explained: "It greatly increases efficiency... I can focus on value-adding aspects. I'm able to focus on something that adds value."

Be aware of potential dependency: Multiple participants were cautioned about the risk of over-reliance. Participant 8 noted: "There's a risk of dependency... At some point, it might hinder your development."

Learn effective prompting: Some participants suggested that the value derived from AI depends significantly on how questions are formulated. Participant 7 observed that many people use AI for fundamental purposes when it could be employed much more effectively with better prompting strategies.

These recommendations reflect a pragmatic approach to AI integration, embracing its benefits while remaining mindful of its limitations and maintaining human oversight of critical product decisions. The overwhelming consensus was that GenAI represents a powerful tool that, when properly integrated, can significantly enhance product management capabilities without replacing the core human judgment that defines the profession.

5. DISCUSSION

This research examined how product managers incorporate GenAI tools into their ideation processes and the unintended consequences that result from this integration. The findings reveal a nuanced landscape where product managers actively navigate the benefits and limitations of these emerging technologies in their daily workflows. This discussion section interprets these findings within broader theoretical frameworks, extracts practical implications, and offers managerial recommendations for organizations seeking to optimize AI integration in product development.

5.1 Theoretical Contributions

This study makes several important contributions to the theoretical understanding of how AI technologies reshape creative professional work, particularly within product management.

First, the research extends the Science, Technology, and Society (STS) literature by providing empirical evidence of how AI technologies are integrated into knowledge work practices, specifically in creative ideation processes. Traditional STS frameworks have examined how technologies mediate human practices and reshape professional roles (Orlikowski, 2007; Pinch and Bijker, 1984). However, relatively little empirical work has documented how AI systems specifically influence creative knowledge work. This study addresses this gap by illuminating the sociotechnical reconfiguration of product management through the adoption of GenAI. The findings show that rather than wholesale replacement of human functions, AI technologies are being positioned as "assistants," "accelerators," and "input machines," complementary actors in creative processes that preserve human agency while augmenting specific capabilities.

The observation that all participants view AI as a complementary force rather than a replacement extends STS theories of technological mediation by demonstrating how professionals actively negotiate their relationships with emerging technologies. The product managers in this study did not passively accept AI capabilities. However, they developed sophisticated integration strategies that preserve their professional identity while leveraging the affordances of AI. This result supports Orlikowski's (2007) view that technologies emerge in practice through active human engagement rather than predetermined technological imperatives.

Second, the research contributes to creativity theory by identifying a previously underexplored phenomenon: GenAI-induced creativity fixation. While creativity literature has extensively documented various forms of cognitive fixation that inhibit creative thinking (Smith, 1995; Jansson and Smith, 1991), the specific ways AI systems might induce fixation represent a novel theoretical contribution. The findings reveal that dependency on AI tools can gradually reshape cognitive habits, potentially atrophying independent creative thinking. This result extends theoretical models of creativity by identifying a new source of creative constraint emerging from human-AI interaction.

The findings regarding standardization of innovation further contribute to creativity theory by demonstrating how AI systems trained on similar datasets may produce homogenized outputs across users and organizations. This result suggests that widespread AI adoption without critical intervention could potentially reduce the diversity of ideas in the marketplace—a concerning implication for innovation theory, which emphasizes the importance of variation in evolutionary innovation processes (Nelson and Winter, 1982). The observation that different AI systems produce similar outputs across participants suggests potential systemic limitations in how these technologies currently support creative processes.

Third, this research advances the theoretical understanding of human-AI complementarity by empirically documenting the specific task domains where each excels. The findings reveal that AI currently demonstrates strengths in information synthesis, pattern recognition, and linguistic refinement. At the same time, humans maintain advantages in contextual understanding, strategic vision, and breakthrough innovation. This empirical mapping of complementary capabilities contributes to emerging theories of human-AI collaboration (Daugherty and Wilson, 2018) by providing a domain-specific analysis of how these partnerships function in practice within product ideation contexts.

Another theoretical contribution is identifying what might be termed "AI literacy". The findings show that experienced product managers develop sophisticated mental models for effective AI integration, including knowing when to consult AI, framing queries, and critically evaluating outputs. This result extends theories of technological literacy (Selber, 2004) by identifying the competencies required for effective human-AI collaboration in creative professional contexts.

Ultimately, the research contributes to the development of ethical frameworks for AI by identifying key tensions in data privacy, intellectual property, and epistemic authority that arise in real-world professional applications. The findings reveal that product managers actively negotiate complex trade-offs between AI utility and data protection, developing informal norms and personal risk management strategies in the absence of formal organizational guidelines. This empirical documentation of emerging ethical challenges contributes to normative theories of responsible AI by grounding abstract principles in concrete professional practices.

5.2 Practical Implications

The findings of this study have several significant practical implications for product managers and organizations seeking to integrate GenAI tools into their ideation processes.

The research reveals specific task domains where GenAI tools deliver the highest value, enabling product managers to allocate their AI usage for maximum benefit strategically. Based on the participants' experiences, GenAI tools demonstrate particular strengths in documentation and formalization, where all participants found significant value in using AI to draft, structure, and refine documentation such as PRDs, task descriptions, and meeting notes, with Participant 9 noting, "I use it extensively for Jira tasks and documentation," suggesting that routine documentation tasks are prime candidates for AI assistance. Communication enhancement emerged as another strength, with multiple participants highlighting AI's value in improving written communication and cross-functional collaboration, exemplified by Participant 5's experience using AI to "help prepare task descriptions for the design team that uses appropriate design terminology," demonstrating how AI can bridge terminology gaps between teams, while Participant 1's use of AI to make "document content more formal" shows its utility in professionalizing communication. Information synthesis represents another valuable application, as several participants valued AI's ability to organize, summarize, and extract insights from complex information, illustrated by Participant 4's use of AI to "summarize notes from developers," showing how AI can make information more accessible and actionable. For ideation support, while participants were skeptical of AI's ability to generate innovative ideas, many found value in using it to expand thinking and overcome initial creative blocks, demonstrated by Participant 5's extensive use of AI for brainstorming "How can we do this? How can we solve this problem?" which shows its utility in initial ideation phases. Additionally, user-facing content creation proved particularly valuable, as Participant 5 found AI to be "exceptionally useful for creating user-facing messages, error messages, and other interface text," suggesting a particular value in crafting concise, purpose-driven communication.

However, the findings also identify apparent limitations in current GenAI capabilities, indicating domains where human judgment should remain primary. Breakthrough innovation represents an explicit limitation, as all participants agreed that AI failed to deliver radical innovation, suggesting that truly novel concept development should remain primarily human-driven. Strategic decision-making also requires human oversight, with multiple participants expressing reluctance to use AI for high-stakes strategic decisions, as Participant 5 stated they would "never go to business stakeholders with AI-generated content without significant editing." Domain-specific understanding poses another challenge, with participants noting AI's struggles with contextual adaptation. For instance, Participant 3 observed that AI "can't produce ideas tailored to a specific product's pattern because it does not know the context." Finally, analytical depth remains insufficient, as several participants found AI's analyses superficial; for instance, Participant 5 noted that "the analysis lacks depth when benchmarking competitors." These findings suggest a practical task allocation framework for product managers seeking to optimize AI integration, using AI primarily for routine, structured tasks while preserving human focus for creative, strategic, and contextually complex activities.

The study also provides practical guidance for mitigating the unintended consequences of GenAI adoption identified in the research. Preventing creativity fixation requires product managers to deliberately preserve independent thinking to counteract potential fixation effects, as demonstrated by Participant 3's practice of thinking independently before consulting AI "to avoid bias," which represents a practical strategy for maintaining creative autonomy while benefiting from AI assistance. Countering standardization becomes essential to avoid the homogenization of ideas observed in the study, requiring product managers to deliberately implement strategies to differentiate their thinking. This argument is exemplified by Participant 5's approach, which involves finding information through traditional research before asking AI to interpret it, representing a practical method for maintaining originality. Managing trust appropriately addresses the factual accuracy concerns highlighted by participants, suggesting that consistent verification processes are necessary. This argument is exemplified by Participant 4's attempt to "get references when AI answers so that I can cross-check," which demonstrates a practical verification strategy. However, the limitations in AI's ability to provide proper citations remain a challenge. Protecting sensitive information addresses the data security concerns expressed by participants, highlighting the need for practical safeguards. This issue is illustrated by Participant 4's unwritten rule, "not to mention my company name to AI tools," which represents a simple yet effective approach to limiting potential data exposure. Developing appropriate reliance patterns reflects the differentiated approaches to AI reliance observed in the study, suggesting that product managers should develop task-specific integration strategies, as exemplified by Participant 4's higher reliance on AI for "routine tasks like drafting documentation" while maintaining human primacy for "strategic decisions or creative direction," representing a practical reliance framework. These practical implications provide actionable guidance for product managers seeking to maximize the benefits of GenAI while mitigating its limitations and potential downsides.

For private sector organizations, this research offers several strategic implications. Competitive differentiation challenges arise from the findings regarding the standardization of innovation, suggesting that organizations heavily reliant on AI for ideation may face difficulties in maintaining distinctive product offerings. As Participant 1 observed when using different GenAI tools, "the results were very similar," indicating potential homogenization risks that could undermine competitive differentiation. Efficiency opportunities present significant potential, with substantial efficiency gains reported by participants. For instance, Participant 2 noted that tasks typically taking three days could be completed in half a day with the assistance of

GenAI, highlighting productivity opportunities for organizations that effectively integrate these tools. Skills development needs become apparent through the emergence of new requirements for effective AI integration, suggesting that organizations should invest in developing what might be termed "AI literacy" among product teams. The sophisticated integration strategies developed by experienced participants indicate that effective AI use requires both technical understanding and metacognitive awareness. Governance gaps represent a critical concern, with the observation that all participants lacked formal organizational guidelines for GenAI usage highlighting a significant gap that organizations should address to manage risks effectively, as AI becomes more deeply integrated into product development processes, making formal governance frameworks increasingly necessary to manage data security, intellectual property, and ethical concerns. Collaboration reconfiguration emerges from findings regarding AI's impact on team dynamics, suggesting that organizations must reconsider how collaboration occurs in AI-augmented environments. This point is exemplified by Participant 5's experience of using AI to "bridge communication gaps between technical and non-technical team members," which points to potential new collaboration patterns enabled by these technologies. These implications suggest that private sector organizations should approach GenAI integration strategically rather than tactically, considering broader organizational implications beyond individual productivity gains.

5.3 Managerial Recommendations

Based on the study findings, several specific recommendations emerge for managers seeking to optimize GenAI integration in product development:

The lack of formal guidelines reported by all participants highlights the need for organizations to develop comprehensive AI governance frameworks. Specific recommendations include establishing clear data security protocols, where organizations should outline explicit guidelines regarding the types of company information that can be shared with external AI systems. This recommendation addresses concerns from Participant 4 regarding the mention of company names and roles. It provides clear guidelines for sharing appropriate information. Organizations must establish intellectual property frameworks that develop clear approaches to ownership attribution for AI-assisted innovations, given the diverse perspectives on IP risks observed in the study. These frameworks should clarify when legal verification is required, as demonstrated in the case described by Participant 5, where AI suggested potentially trademarked terminology. Implementing verification standards becomes essential to address the factual accuracy concerns raised by multiple participants, requiring organizations to establish precise verification requirements for AI-generated information used in consequential decisions and specify when additional research is required to validate AI outputs.

Developing ethical guidelines represents another crucial component, with organizations establishing principles for maintaining appropriate human oversight of AI-assisted processes, ensuring transparency about AI contributions in presented work, and preserving the diversity of thought in ideation processes. Creating regular review mechanisms addresses the rapidly evolving nature of GenAI technologies, requiring organizations to implement periodic assessments of AI's impact on product differentiation and update governance policies as capabilities evolve.

The study findings suggest specific approaches for designing workflows that effectively leverage both human and AI capabilities. Organizations should implement deliberate sequencing based on successful patterns observed among participants, encouraging ideation processes that begin with independent human thinking before incorporating AI assistance. This sequencing preserves creative autonomy while still benefiting from AI's expansive capabilities. Additionally, developing contextual enrichment practices becomes crucial given the findings regarding AI's struggles with domain-specific understanding, requiring organizations to develop systematic approaches to providing rich context, exemplified by Participant 5's experience creating and providing a matrix to AI when working on a mobile highlight module, which demonstrates how structured input can improve output quality.

Creating collaborative filtering mechanisms represents another essential workflow element, with Participant 5's collaborative approach with UX writers exemplifying an effective workflow pattern that organizations could formalize and scale. Organizations must establish an appropriate division of labor by explicitly designing workflows that allocate tasks based on the complementary strengths of humans and AI, as identified in the study. This approach leverages AI primarily for information synthesis, pattern recognition, and linguistic refinement. At the same time, humans focus on empathy, contextual understanding, strategic vision, and breakthrough innovation.

Finally, developing AI literacy training becomes essential as the sophisticated integration strategies developed by experienced participants suggest organizations should invest in formal training to develop practical AI utilization skills across product teams. This training should encompass both technical aspects, such as effective prompting, and metacognitive aspects, including appropriate reliance patterns, ensuring teams can maximize the benefits of human-AI collaboration while maintaining the quality and creativity of their ideation processes.

The findings regarding the risks of standardization and homogenization suggest specific recommendations for maintaining creative differentiation. Organizations should implement diversity-promoting ideation practices by establishing deliberate practices to counter potential homogenization effects, such as conducting initial ideation sessions without AI before introducing AI assistance, while developing differentiation-focused evaluation criteria where review processes for AI-assisted ideation explicitly assess whether outputs transcend obvious or generic solutions, identifying opportunities for human enhancement of standardized suggestions. Additionally, encouraging cross-domain inspiration becomes essential, given AI's tendency to provide limited examples from obvious sources, as noted by Participant 5 in the context of benchmarking. This point requires organizations to deliberately promote cross-domain inspiration-seeking that transcends the current limitations of AI.

Organizations must preserve space for radical innovation by maintaining dedicated processes for exploring breakthrough innovations that deliberately minimize AI dependence, given the unanimous observation that AI fails to deliver radical innovation. Furthermore, developing complementary tool strategies addresses the observation that different AI tools produce similar outputs, suggesting organizations should explore using diverse AI tools with different training foundations alongside traditional creativity methods to maximize creative diversity and avoid standardization pitfalls.

These managerial recommendations offer actionable guidance for organizations looking to harness the efficiency benefits of GenAI while preserving the creative differentiation necessary for a competitive edge in product development. They ensure that the integration of AI tools enhances, rather than diminishes, the innovative capacity of their product development processes.

6. CONCLUSION

This study investigated how product managers integrate GenAI into their ideation processes and identified the unintended consequences of this integration. We gained insights into the complex interplay between AI technologies and creative knowledge work in product development contexts through in-depth interviews with twelve product managers. This conclusion summarizes the key findings, addresses the research questions, and outlines limitations and directions for future research.

6.1 Summary of Key Findings

The research revealed several significant patterns in how product managers are incorporating GenAI into their workflows:

First, all participants had integrated GenAI tools, predominantly ChatGPT, into their daily work processes, with usage frequencies ranging from several times daily to every few days. This integration followed diverse adoption paths, with some participants motivated by concerns about efficiency, others by curiosity about emerging technologies, and some influenced by their colleagues' successful applications. Regardless of motivation, participants consistently positioned AI as a complementary force rather than a replacement, characterizing it as an "assistant," "accelerator," or "input machine."

Second, GenAI tools demonstrated clear strengths in specific task domains while showing limitations in others. Participants found AI particularly valuable for documentation and content formalization, enhancing communication across functional boundaries, synthesizing information, supporting ideation, and creating user-facing content. However, they unanimously agreed that AI failed to deliver radical innovation or deep analytical insights, highlighting fundamental limitations in GenAI's ability to transcend existing patterns and generate novel ideas.

Third, despite productivity gains, with some participants reporting that tasks previously taking days could be completed in hours, the research identified several unintended consequences of GenAI integration. The most prevalent was creativity fixation, where AI potentially constrained rather than enhanced creative thinking over time. Ten of twelve participants expressed concerns that their creativity was negatively affected through regular AI use, with some noticing a progression from initial creative enhancement to eventual dependency. Other unintended consequences included the standardization of innovation, decision-making biases, and challenges in information verification.

Fourth, Efficiency vs. Creativity: The findings revealed a fundamental tension between efficiency gains and creative originality. While participants consistently reported significant productivity improvements. The research suggests that the uncritical prioritization of efficiency through AI assistance may gradually erode the creative differentiation essential for achieving a competitive advantage in product development. Organizations face the critical challenge of balancing speed improvements against the need for breakthrough thinking that transcends AI-generated standardization.

Fifth, Decision-Making Risks: The study uncovered patterns concerning how AI affects decision processes, with evidence of over-reliance potentially limiting critical thinking. Participant 5's admission of feeling compelled to "consult it even when I know the answer" exemplifies how dependency can develop even among experienced professionals. More troubling were verification challenges, with Participant 4 acknowledging sometimes using AI as a source "even when I can't verify the information." This epistemic vulnerability suggests that as AI becomes increasingly embedded in product management workflows, critical evaluation skills may atrophy in favor of algorithmic deference. Organizations must develop explicit verification frameworks and cultivate metacognitive awareness to maintain rigorous decision-making in the face of increasing AI integration.

Sixth, B2B vs. B2C Product Management Experiences: The study revealed notable differences in how product managers in B2B versus B2C contexts experienced and utilized GenAI. B2B product managers reported more extensive use of AI for technical documentation and cross-functional communication. Participant 2 noted AI's value in "bridging terminology gaps between business and technical teams." These participants emphasized AI's utility in translating complex technical concepts into language accessible to different stakeholders, a critical challenge in B2B environments where products often involve multiple specialized teams.

In contrast, B2C product managers emphasized the role of AI in user-facing content creation and understanding user perspectives. Participant 5 highlighted using AI extensively for "creating user-facing messages, error messages, and other interface text." At the same time, Participant 9 described leveraging AI to analyze user research data. However, these participants also noted significant limitations in AI's ability to accurately represent user perspectives. Participant 5 observed that AI "has a certain language style that it can't deviate from, even when attempting to generate content for different user personas."

The difference extended to risk perceptions as well. B2B product managers showed greater concern about data security risks. Participant 4 mentioned an "unwritten rule not to mention my company name to AI tools" due to business relationship sensitivities. B2C managers, on the other hand, expressed more concern about AI's limitations in capturing consumer trends, with Participant 5 finding AI outputs to be "outdated thoughts" that failed to reflect current market dynamics. These variations suggest that practical GenAI integration approaches may need to be tailored to the specific challenges of B2B versus B2C product development contexts.

Seventh, experienced product managers have begun developing sophisticated adaptation strategies to maximize AI benefits while mitigating limitations. These include thinking independently before consulting AI, implementing context-specific reliance patterns, developing collaborative filtering approaches, and maintaining strategic task allocation between human and AI capabilities. These emerging practices represent an intuitive development of "AI literacy," the metacognitive ability to discern where AI inputs add the most value and where human judgment remains essential.

Finally, the study uncovered significant ethical and intellectual property concerns that organizations have yet to address systematically. Despite widespread adoption, none of the participants reported formal company guidelines for GenAI usage, leading to the organic development of personal risk management strategies based on individual judgment and informal norms. This governance gap underscores a pressing need for robust organizational frameworks to manage data security, intellectual property, and information verification as AI becomes increasingly integrated into product development processes.

6.2 Addressing Research Questions

This study set out to address three primary research questions:

RQ1: How does generative AI impact product ideation in new product development?

The findings reveal that generative AI has a multifaceted impact on product ideation, transforming the process and outcomes of creative development work. On the positive side, GenAI significantly accelerates ideation activities, with participants reporting substantial efficiency gains in documentation, communication refinement, and initial idea exploration. All twelve participants noted that AI enables them to accomplish tasks in a fraction of the time previously required, reducing what might have been days of work to hours. This acceleration particularly benefits the early stages of ideation, helping product managers overcome initial creative blocks and quickly generate starting points for further development.

Beyond time savings, GenAI enhances ideation processes through improved information synthesis and cross-functional communication. Participants described using AI to bridge terminology gaps between teams, make technical concepts more accessible to non-technical stakeholders, and integrate insights from diverse sources. Participant 5's experience using AI to "help prepare task descriptions for the design team that uses appropriate design terminology" exemplifies how AI facilitates more effective collaboration across disciplinary boundaries.

However, the impact on idea quality and originality appears more problematic. All participants unanimously agreed that GenAI failed to deliver radical innovation or breakthrough thinking. Participant 3 bluntly stated that AI is "not innovative," merely presenting "things that have been known in the market for a long time, compiled and collected." Participant 6 noted that AI "usually just lists the first three options that would come to anyone's mind." Participant 5 highlighted limitations in persona-based content generation, observing that "AI has a certain language style that it can't deviate from, even when attempting to generate content for different user personas," indicating its inability to authentically represent diverse user viewpoints, a critical capability for user-centered product design. These limitations are a fundamental constraint in current AI systems' ability to transcend existing patterns and generate truly novel concepts, a critical limitation for product innovation processes that depend on differentiation.

The research suggests that GenAI's most beneficial impact on product ideation occurs through complementary integration patterns where AI handles routine, structured tasks. At the same time, humans maintain primacy in areas that require creativity, contextual awareness, and strategic judgment. The most successful approaches position AI as an "accelerator" or "assistant" that enhances human capabilities rather than replacing them. AI contributions serve as inputs to human creative processes rather than final solutions.

RQ2: What are the unintended consequences of using generative AI for ideation?

The research identified several significant unintended consequences of GenAI integration in product ideation:

GenAI-induced creativity fixation: Perhaps the most concerning finding was the potential for AI to gradually reshape cognitive habits, potentially atrophying independent creative thinking over time. Participants expressed concerns about the adverse effects of regular AI use on their creativity. Participant 5 articulately described this evolution: "I initially thought it helped my creative process, but now I find myself going straight to AI without thinking first, which has reduced my creativity." This sentiment was echoed by Participant 9, who admitted to developing a compulsive checking behavior: "I've become somewhat dependent on it. I must consult it even when I know the answer, thinking it might suggest something better." Participant 8 framed this dependency as a comfort issue with potentially troubling implications: "Having something like a personal assistant constantly at your side is very comfortable. But if we ever lost access to it... that's concerning." This progression from initial creative enhancement to psychological dependency suggests a concerning trajectory where convenience may gradually erode creative capabilities and foster reliance patterns that extend beyond mere practical utility.

Standardization of innovation: The uniform outputs produced by GenAI tools across different users and even different AI systems raised concerns about the potential homogenization of product ideas. Participant 1 discovered that "when using two different GenAI tools, the results were very similar," suggesting standardization extends across AI systems. Participant 6 observed this homogenization directly when interviewing candidates who had used AI for their application materials: "Their mockups were remarkably similar." This standardization prompted a cautious approach to AI outputs, with participants consistently emphasizing the importance of critical evaluation and analysis. Participant 4 stated, "I never use AI output directly; I always need to adapt it to our specific context and constraints," Participant 9 affirmed, "I've never had a situation where I thought, 'This is so good I can use it directly'" This skepticism reflected limited trust in AI's originality and a conscious effort to mitigate standardization risks. The similarity in AI-generated content across users and systems suggests that widespread AI adoption without critical intervention and substantial human oversight could lead to a reduction in the diversity of ideas in the marketplace.

Decision-making biases: Participants encountered significant challenges in verifying AI-generated information, often finding themselves relying on potentially unverified information in their decision-making processes. Participant 4 admitted, "Sometimes I have to use it as a source even when I can't verify the information," potentially propagating misinformation through decision chains. The inability of AI to provide proper citations or references exacerbated these verification challenges, creating what Participant 8 described as a verification dilemma: "If it's something I don't know much about, if I'm not an expert in that domain, I become dependent on it. Sometimes, I can't even cross-check with Google searches." This issue led to varying levels of trust. Participant 5 expressed skepticism after a troubling experience: "It gave me wrong information about astrology, then immediately admitted its mistake, which made me question what other errors it might be making that I'm not catching." Participants primarily used GenAI to enhance their existing ideas to mitigate these risks rather than as a primary decision-making tool. Participant 3 likened using AI to an "input machine," emphasizing that they "never use the results 100%; I evaluate them using my own experience too." Similarly, Participant 5 noted a preference for "to find information through traditional means and then using AI to help interpret or apply that information to my specific context, rather than relying on AI as the primary information source." This approach positioned AI as one input among many in decision processes, with participants maintaining final judgment authority while leveraging AI for idea refinement rather than delegating actual decision-making to the technology.

Team dynamics shift: AI integration introduces new patterns in team collaboration, sometimes bridging communication gaps but creating new forms of authority contestation. Participant 4 observed that "when I mention ChatGPT as a source in team discussions, there's often pushback and requests for additional research," indicating organizational skepticism toward AI-sourced information. Participant 5 found that when presenting AI-generated naming suggestions to senior management and the legal team, they were met with skepticism and concerns about potential trademark infringement. These experiences suggest emerging social norms around AI attribution that influence how information is evaluated in organizational contexts.

Ethical and IP tensions: The integration of GenAI created unresolved tensions around data security, intellectual property, and epistemic authority. Participant 4 revealed an unwritten organizational rule: "I have an unwritten rule not to mention my company name to AI tools." At the same time, Participant 5 described an incident where AI suggested potentially trademarked product category names. These issues highlight the complex ethical terrain product managers must navigate without formal guidelines.

These unintended consequences highlight the complex sociotechnical implications of GenAI adoption in knowledge work contexts, where technologies designed to enhance human capabilities may simultaneously introduce new constraints and challenges that require conscious management.

RQ3: How do product managers perceive and navigate these unintended consequences?

The study revealed that product managers are developing sophisticated strategies to manage the unintended consequences of GenAI. However, these approaches remain primarily individual and informal rather than organizationally structured.

Awareness development: The participants demonstrated varying levels of awareness regarding the potential adverse effects of AI. Some, like Participant 5, explicitly recognized the development of dependency: "I feel like it's making me dumber because I now instinctively want to ask AI before thinking for myself." Others, like Participant 7, showed proactive awareness: "I'm quite obsessed with these topics... I try not to rely too heavily on AI for this reason." This metacognitive awareness appears to be a precondition for developing effective mitigation strategies.

Intentional limitation strategies: To preserve creative autonomy, participants described deliberate boundaries around AI usage. Participant 3 emphasized the importance of thinking independently before consulting AI "to avoid bias." At the same time, Participant 5 developed domain-specific limitations, noting, "For creative tasks, I prefer researching on Google or reading Medium articles instead of relying on AI." Participant 8 stated: "I'm quite meticulous about not overusing it... I try not to rely on calculators much, either. I prefer to multiply numbers in my head." These self-imposed limitations reflect conscious efforts to maintain cognitive independence.

Task-specific reliance patterns: Participants developed nuanced frameworks for when to rely heavily on AI versus when to maintain human primacy. Participant 4 noted that a higher reliance was acceptable for "routine tasks like drafting documentation," while maintaining that "for strategic decisions or creative direction, human judgment remains primary." These patterns reflect sophisticated contextual judgment about the appropriate levels of automation.

Process refinement approaches: To counter standardization risks, participants developed process modifications that positioned AI as one input among many rather than a singular source. Participant 5's collaborative filtering approach with UX writers exemplifies this: "With UX writers, we use AI suggestions as options to select from rather than final solutions." Participant 7 described first thinking independently: "I try to think of some ideas myself before asking, without assistance... After comparing what I've thought of with what comes back, a concept forms in my mind." These approaches maintain human creative primacy while leveraging AI's expansive capabilities.

Information verification protocols: To address concerns about factual accuracy, participants developed personal verification strategies to ensure the accuracy of their information. Participant 4 described asking for references: "I try to get references when AI answers so I can cross-check." Participant 9 noted: "If I'm asking it to calculate something, I cross-check those calculations." These self-developed verification approaches indicate awareness of AI's limitations in providing reliable information.

Security practices: For data protection, participants developed personal safeguards. Participant 8 described limiting information sharing: "I generally don't share much data or specific information about our systems." Participant 9 mentioned using incognito sessions: "Sometimes I close the session when looking at sensitive information. It might seem silly, but I don't want to use that information for my model."

These navigation strategies suggest product managers are developing what might be called "AI literacy," the metacognitive ability to discern where AI inputs add value and where human judgment remains essential. However, the individual and informal nature of these strategies highlights the need for more structured organizational approaches to support effective AI integration as these tools become increasingly embedded in product development processes.

6.3 Limitations and Future Research

This study offers valuable insights into integrating GenAI in product ideation processes; however, several limitations should be acknowledged.

The research focused on product managers from a specific organizational context, which may limit the applicability of these findings to other settings. The study's qualitative approach yielded rich insights; however, the sample size of twelve participants from a single e-commerce company represents a limitation on the broader applicability of the results. While thematic saturation was achieved on key issues, these patterns may not be consistent across different industries, company sizes, or cultural contexts.

The rapidly changing nature of GenAI technologies also means that the challenges and opportunities identified here may shift as capabilities advance. What product managers face today with current AI tools may look quite different as these technologies continue evolving at their current pace.

Future research should investigate how these dynamics unfold across diverse organizational settings and monitor changes over time through longitudinal studies. A broader sample spanning multiple industries and company types would help verify whether the patterns observed here reflect broader trends in GenAI adoption or are specific to particular contexts.

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APPENDICES

APPENDIX A: Overview of Research Participants

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Table A.1: Participant List.

Number	**Name**	**Position**
E1	Anonymous	Lead Product Manager
E2	Anonymous	Product Manager
E3	Anonymous	Senior Product Manager
E4	Anonymous	Senior Product Manager
E5	Anonymous	Senior Product Manager
E6	Anonymous	Product Manager
E7	Anonymous	Senior Product Manager
E8	Anonymous	Product Manager
E9	Anonymous	Product Manager
E10	Anonymous	Lead Product Manager
E11	Anonymous	Product Manager
E12	Anonymous	Product Manager

APPENDIX B: Semi-Structured Interview Guide

APPENDIX B: Semi-Structured Interview Guide

Semi-Structured Interview Protocol for Research on the Unintended Consequences of Generative AI in Product Ideation

Target Participants:

- Product Managers with at least 3 years of experience in new product development.
- Experience using AI-driven ideation tools (e.g., ChatGPT, Midjourney, Gemini, Copilot, etc.).
- Working in B2B (e.g., SaaS, enterprise solutions, industrial products) or B2C (e.g., e-commerce, consumer goods, digital platforms, retail) companies.

Interview Questions

Section 1: Background and Role of the Product Manager (10 min)

1. Could you briefly introduce yourself and your role?
    - How long have you been working as a product manager?
    - What type of products do you work on (B2B or B2C)?
    - How does ideation typically happen in your product development process?
2. Have you or your team used Generative AI tools for product ideation?
    - If yes, which tools (e.g., ChatGPT, Midjourney, Jasper, Stable Diffusion)?
    - How frequently do you use these tools in ideation?
    - What motivated the adoption of Generative AI in your process?

Section 2: Impact of Generative AI on Product Ideation (15-20 min)

3. How do Generative AI tools contribute to product ideation?
    - Do they help generate new ideas, refine existing ones, or both?
    - Are there specific types of ideas where AI is beneficial?
4. What are the key advantages of using Generative AI in ideation?
    - Does it speed up brainstorming?

- Does it help overcome creative blocks?
- How does it impact collaboration within your team?

5. Have you observed any patterns or biases in AI-generated ideas?
    - Do the AI-generated ideas tend to be repetitive or similar to past trends?
    - Are there cases where AI reinforces existing industry norms rather than creating breakthrough innovations?
6. How do you balance human creativity with AI-generated ideas?
    - Do you take AI suggestions at face value or refine them significantly?
    - Have you ever encountered situations where team members unquestioningly accepted AI outputs?

Section 3: Unintended Consequences of Generative AI in Ideation (20 min)

7. Have you encountered any unexpected or unintended consequences of using Generative AI for ideation?
    - If yes, can you describe an instance?
8. Creativity Fixation:
    - Have you noticed that Generative AI narrows down ideation rather than expanding possibilities?
    - Do team members become overly reliant on AI suggestions, limiting their independent thinking?
9. Standardization of Innovation:
    - Do AI-generated ideas tend to align with conventional or mainstream industry trends rather than disruptive innovations?
    - Have you ever rejected an AI-generated idea because it felt too generic?
10. Decision-Making Biases and Automation Reliance:
    - Have you or your team faced challenges in critically evaluating AI-generated ideas?
    - Have you experienced automation bias (e.g., trusting AI suggestions without questioning their validity)?

- How does AI impact team discussions and final decision-making on product direction?

11. Ethical and Intellectual Property Concerns:

    - Who owns the rights to AI-generated product ideas? Have you faced legal concerns in your company?

    - Have you encountered issues where AI-generated outputs resembled competitors' products or existing patents?

    - Do you feel that AI-generated ideas could lead to ethical dilemmas in product development (e.g., misleading customers, bias in AI outputs)?

Section 4: Managing the Risks and Future Outlook (15 min)

12. How does your organization manage the risks associated with Generative AI in ideation?

    - Are there any internal guidelines or policies regarding the use of AI-generated ideas?

    - Have you or your team rejected AI-generated ideas due to concerns about quality or ethics?

13. Do you see Generative AI as a long-term tool for product ideation, or do you think its role will diminish over time?

    - How do you think the role of product managers will evolve as AI becomes more prevalent in ideation?

    - Do you foresee AI complementing or replacing certain aspects of ideation in the future?

14. What advice would you give other product managers considering Generative AI for ideation?

Closing Remarks (5 min)

15. Is there anything else you want to add about your experience with AI in ideation?

16. Would you be open to a follow-up discussion if needed?

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- **B.Sc. :** 2016, Yıldız Technical University, Faculty of Mechanical Engineering, Industrial Engineering
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