Adopting Generative AI in Industrial Product Companies: Challenges and Early Pathways

Research Paper

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Abstract. Generative Artificial Intelligence (GenAI) is rapidly transforming industries, yet its adoption in industrial product companies remains fraught. Unlike software and service firms, they often lack digital expertise, are challenged with legacy systems, and operate in a complex environment of hardware, software, and service. While the hype surrounding GenAI promises future breakthrough innovation, industrial product companies must navigate intricate challenges to realize its full impact. This study, based on expert interviews with industry leaders and GenAI technology providers, identifies nine key challenges and corresponding countermeasures that shape GenAI adoption in industrial product companies. By structuring these insights across core dimensions - technology, organization, and environment - we bridge the gap between expectation and execution, offering practical guidance for firms seeking to move beyond experimentation toward meaningful value creation. Our findings contribute to a deeper understanding of the nuanced adoption processes of GenAI in industrial contexts.

Keywords: *GenAI, AI Adoption, Industrial Product Companies, AI in Manufacturing, Digital Transformation*

1 Introduction

The rapid emergence of generative artificial intelligence (GenAI) significantly disrupted organizational practices (McAfee et al., 2023; Solaiman et al., 2023). Unlike other modern technological innovations (e.g., mobile computing or cloud) that settled in consumer practices well in advance of business practices, the speed and decisiveness of GenAI adoption in industrial product companies (IPCs) is unprecedented (Bain, 2024b). While previously foremost BigTech software companies entered and embraced technological innovations with significant investments early stage, with GenAI, also industrial product companies and their managements showcased great determination and conviction in adopting this technology. For example, leading industrial product companies such as Bosch or Siemens invested significant resources in GenAI startups, ventured own GenAI solutions, or entered strategic partnerships with technology pro-

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viders (e.g., NVIDIA, Microsoft, or AWS) (Bosch, 2023, 2024; NVIDIA, 2022; Siemens, 2024). Ultimately, IPCs take a decisive forward-looking approach to adopting GenAI, yet they still face significant challenges in fully integrating it across their value chains and scaling its adoption (Sebastian et al., 2020). Accompanying these real-world dynamics, the IS community is well-positioned to examine the intricate dynamics involved in IPCs adopting GenAI (Berente et al., 2021). IS research contributes a comprehensive portfolio of technology adoption frameworks (Rogers, 1995; Tornatzky & Fleischer, 1990), best practices (Johnston & Mehra, 2001; Zhou & McLaren, 2014), and strategies (Abdelghaffar et al., 2024; Kapupu & Mignerat, 2015), that have guided organizations in generating competitive advantage through technology.

However, the trajectory of GenAI adoption is markedly distinct. Rather than the gradual, cautious uptake observed with earlier innovations, top-level executives in IPCs are making GenAI their top priority (Bain, 2024a). Yet, unlike software and service firms, IPCs often lack digital expertise, are challenged with legacy systems, and operate in complex environments integrating hardware, software, and service (Al-kfairy, 2025; Anderson et al., 2022). Moreover, GenAI's potential to democratize AI access (Seger et al., 2023) and its emergence as the next *"horizontal enabling layer"* (Bezos, 2024), boost productivity among both AI experts and non-experts, which distinguishes its adoption pattern from that of other technologies.

Altogether, reflecting on the complexity of GenAI technology and the view that inaction could pose an existential threat (Singh et al., 2024), industrial product companies are actively seeking strategies to integrate and leverage GenAI while confronting unprecedented organizational, technical, and environmental challenges (Schneider et al., 2024). To support their shift from experimentation to value-generating application, scholars and practitioners need a clearer view of both the obstacles that arise inside industrial settings and the strategic levers that successfully mitigate them. Hence, we investigate (RQ1): *"What challenges do industrial product companies face in adopting Generative AI? And (RQ2): What strategies do industrial product companies adopt to overcome these challenges?"*

Following seminal IS research on technology and AI adoption (e.g., Hamm & Klesel, 2021; Madan & Ashok, 2023; Oliveira & Martins, 2011), we utilize the technology–organization–environment (TOE) framework to provide a structured approach analyzing adoption challenges at the firm level (Tornatzky & Fleischer, 1990). We conducted an interview study (Myers & Newman, 2007; Schultze & Avital, 2011), integrating the dual perspective of IPCs and GenAI technology providers. This dichotomic conceptualization allows us to examine the challenges and countermeasures associated with GenAI adoption in a holistic manner. More concretely, we identify nine key challenges and corresponding countermeasures related to the adoption of GenAI within industrial product companies.

2 Theoretical Background

2.1 Information Technology Adoption at the Company Level

Information technology adoption has historically catalyzed transformative shifts within organizations and industries (Scott, 1992; Thompson & Bates, 1957; Woodward, 1994). Each technological advancement, such as the IoT, has redefined value creation and operating models (Abdelghaffar et al., 2024; Wlcek et al., 2023). Understanding these dynamics is essential for examining the unique opportunities and challenges posed by emerging technologies like GenAI.

Technology adoption models can be broadly categorized into individual-level models and firm-level models (Oliveira & Martins, 2011). While models such as the Technology Acceptance Model (TAM), the Theory of Planned Behavior (TPB), and the Unified Theory of Acceptance and Use of Technology (UTAUT) are primarily designed to capture individual user acceptance and behavioral intentions, firm-level frameworks account for broader organizational and environmental factors (Ajzen, 1991; Marangunić & Granić, 2015; Oliveira & Martins, 2011; Venkatesh et al., 2012).

At the company level, technology adoption is commonly studied through frameworks such as the diffusion of innovation (DOI) theory (Rogers, 1995) and the TOE framework (Oliveira & Martins, 2011; Tornatzky & Fleischer, 1990). DOI explains how innovations spread over time and identifies firm-level factors influencing adoption, such as leader attitudes, organizational structure, and external openness. In contrast, the TOE framework is particularly well-suited to the present study, as it explicitly integrates the environmental context, encompassing industry dynamics, competitive pressures, and regulatory factors, with technological and organizational considerations. This provides a more comprehensive and empirically validated approach for analyzing intrafirm IT adoption. Similarly, the TOE framework outlines three contexts influencing technological innovation: the technological context (existing and emerging technologies relevant to the firm), organizational context (size, structure, and internal processes), and environmental context (industry dynamics, competitors, and regulatory factors). The TOE framework extends DOI by adding the environmental dimension, providing a robust and empirically validated approach for analyzing intrafirm IT adoption, with applicability across diverse IS innovation studies, including AI and GenAI (Hamm & Klesel, 2021; Kowalczyk et al., 2023; Ronaghi, 2023).

Given the fact that this research focuses on company-level GenAI adoption challenges, the TOE framework was chosen due to its comprehensive consideration of both internal organizational factors and external environmental influences.

2.2 Generative Artificial Intelligence

Generative AI describes the use of models like generative adversarial networks (GANs), variational autoencoders (VAEs), or transformers to autonomously generate new content (Goodfellow et al., 2020; Kingma & Welling, 2019; Vaswani et al., 2017). This emerging technology provides organizations with a tool that can rapidly produce high-quality outputs at minimal cost, offering significant potential for innovation and operational efficiency (Holmström & Carroll, 2024). GenAI has demonstrated applications across various industries, including healthcare, engineering, and business, underscoring its versatility (Feuerriegel et al., 2024; Gozalo-Brizuela & Garrido-Merchán, 2023).

Despite its rapid rise, GenAI remains in its early stages of adoption, with organizations transitioning from experimentation to large-scale deployment. While its potential is widely recognized, its integration into business operations is still ongoing,(BCG, 2024; McKinsey, 2024b; Schneider et al., 2024). Additionally, despite its promising capabilities, organizations face challenges in realizing GenAI's full potential, particularly around technical integration, organizational readiness, and the alignment of GenAI initiatives with broader strategic goals (Al-kfairy, 2025; BCG, 2023; McKinsey, 2024a).

While existing IS and management literature provides rich insights into the potential of GenAI across industries such as education and entrepreneurship (e.g., Hadidi & George, 2023) or specific applications such as coding and chatbots (e.g., Bruhin, 2024; Haase & Hanel, 2023), it provides little detail on the adoption challenges IPCs must overcome in adopting GenAI within their hardware, software, and service business.

It is evident that IPCs encounter analogous challenges in adopting GenAI as other firms in disparate industries, yet the gravity and intricacy of these challenges are particularly pronounced (Anderson et al., 2022). In contrast to financial or software firms, IPCs primarily rely on physical products or product systems that are embedded in highly regulated environments, necessitating a balance between physical safety, strict IP protection, and compliance demands (Porter & Heppelmann, 2014; Wlcek et al., 2024). The capital-intensive nature of their operations, encompassing hardware, software, and service business, in conjunction with their narrow profit margins and prior investments in IIoT and Industry 4.0, underscores the imperative for a meticulous, ROI-driven approach to technology adoption (Porter & Heppelmann, 2014; Wlcek et al., 2024). Consequently, IPCs are compelled to adopt Generative AI with the utmost caution, ensuring that risk mitigation, compliance, and operational integration are executed with unparalleled rigor.

3 Methodology

We conducted an interview study within a diverse set of case companies to explore the adoption of GenAI in industrial product companies (Eisenhardt, 1989; Myers & Newman, 2007; Schultze & Avital, 2011; Yin, 2018). This methodology allows for an in-depth examination of real-world GenAI adoption, evidently reflecting practitioner perspectives of the process, its challenges, and the countermeasures industrial product companies employ.

We used purposeful sampling to construct a diverse and comprehensive case sample representing real-world dynamics (Patton, 2014). While our cases cover ten different industrial sectors, we deliberately concentrated on firms with extensive AI patent portfolios and established digital capabilities. This sampling logic positions the study at the frontier of real-world GenAI practices, focusing on companies with sufficient resources to pursue sustained GenAI adoption as early adopters. As a result, it takes on the perspective of larger incumbents rather than smaller SME firms. More concrete, we selected industrial product companies within diverse industries and different stages of GenAI adoption in order to grasp a comprehensive perspective on the challenges they face. This diverse case selection allows us to derive a broader spectrum of GenAI use cases, eventually attributing more generalizable results (Eisenhardt, 1989; McIntosh & Morse, 2015). We purposely selected companies that build upon significant expertise in digital technology management. In fact, we incorporated the leading AI patent owners in Europe (i.e., C1, C2, C7, C8) and in the US (i.e., C7, C8, C9, C10) (Harrity & Harrity, 2025; QUESTEL SAS, 2023).

We aim to provide a holistic perspective on GenAI adoption in industrial product companies by integrating two expert groups across ten different organizations. First, we build upon insights from experienced, high-ranking managers within different IPCs that contribute profound understanding of IPCs' value creation mechanisms and each organization as a whole. Second, we complement these insights through another set of interviews with technology and domain specialists in leading GenAI technology companies, which typically provide the technical backbone for GenAI initiatives in industrial companies. Integrating both perspectives, we accumulated a rich and nuanced understanding of intra- and interorganizational challenges of GenAI adoption in alignment with the TOE framework (Tornatzky & Fleischer, 1990).

Our data collection comprises 22 semi-structured interviews we conducted with representatives across different management levels (e.g., C-Level, executive, senior manager, and manager) to ensure a diversified and multi-layered perspective on GenAI's organizational impact and adoption processes (Dwivedi et al., 2024). We provide an overview of the conducted interviews in Table 1 below.

The interviews took place from September to December 2024 and lasted on average 59 minutes, varying due to differences in participant availability, role-specific responsibilities, and the natural flow of conversation. In cases where interviews were shorter, our protocol emphasized a focused set of core questions and included probing follow-up queries to ensure that essential insights were thoroughly captured. Participants were asked to reflect on their experiences with GenAI adoption, covering three key themes: (1) professional experiences regarding GenAI adoption and implementation, (2) description of faced challenges, and (3) taken countermeasures to overcome the depicted challenges. In some cases, multiple interviews were conducted within the same organization, either with different roles or the same participant when the initial interview was constrained by time, but the participant had further insights to offer, and the researcher had not yet reached the point of data saturation (Fusch & Ness, 2015). Secondary data sources, including company reports, publicly available statements, and practitioner articles, were also reviewed to complement and validate the findings from the interviews.

Our data analysis was iterative, following an abductive coding process grounded in thematic analysis (Blaikie, 1991; Eisenhardt, 1989). After each interview, key insights were documented and independently reflected upon by multiple researchers before being discussed collectively in order to minimize bias and avoid premature conclusions (Charmaz, 2006). These reflections were then compared against secondary data (e.g., company press releases, annual reports, industry whitepapers, and reputable news articles) to identify emerging themes and patterns related to GenAI's impact on product companies (Eisenhardt, 1989). In alignment with established research on technology adoption, we subsequently mapped these insights onto the TOE framework (e.g., Hamm & Klesel, 2021; Madan & Ashok, 2023; Oliveira & Martins, 2011). Following this approach, we categorized the identified challenges and countermeasures across technological, organizational, and environmental dimensions, enabling a comprehensive examination of the diverse factors influencing GenAI adoption within industrial product companies (Tornatzky & Fleischer, 1990).

Table 1. Overview of interviewed experts

	ID	**Interviewee Position**	**Professional Experience**	**Interview Length**	**Case**
Industrial Product Companies	I01	Executive	~26 years	60 min	C1: Advanced Manufacturing & Engineering
	I02	Executive	~13 years	60 min	
	I03	Senior Manager	~20 years	60 min	
	I04			60 min	
	I05	Senior Manager	~19 years	30 min	
	I06	Senior Manager	~22 years	60 min	
	I07	Manager	~7 years	65 min	
	I08	Senior Manager	~25 years	60 min	C2: Industrial Automation & Energy
	I09	Senior Manager	~21 years	60 min	
	I10	Manager	~11 years	60 min	
	I11	Senior Manager	~10 years	35 min	C3: Automotive
	I12	C-Level	~21 years	60 min	C4: Energy Technology & Industrial Automation
	I13	C-Level	~28 years	70 min	C5: Precision Engineering & Automation
	I14			90 min	
	I15	Senior Manager	~18 years	60 min	C6: Industrial Robotics & Automation
Tech Providers	I16	Executive	~29 years	60 min	C7: Enterprise AI & Cloud Infrastructure
	I17	Executive	~24 years	60 min	
	I18	Senior Manager	~17 years	60 min	
	I19	Senior Manager	~18 years	60 min	C8: Enterprise AI & Cloud Infrastructure
	I20	Manager	~11 years	60 min	C9: Enterprise AI & Cloud Infrastructure
	I21	Senior Manager	~26 years	60 min	C10: Enterprise AI & Cloud Infrastructure
	I22	Manager	~16 years	60 min	

4 Results

Our analysis identifies key challenges industrial product companies face in adopting GenAI. We conceptualized these findings into a triad of challenges composed of technical, organizational, and environmental factors that influence GenAI adoption. Ultimately, IPCs adopting GenAI must address a range of GenAI-specific challenges that extend beyond those encountered in prior technology pushes, including cloud computing, Blockchain, or the IoT. Moreover, IPCs face more pronounced challenges of adopting GenAI in contrast to financial or software firms, ensuring risk mitigation, compliance, and operational integration into their existing hardware, software, and service business.

More concrete, we structure our insights into nine key challenges and corresponding countermeasures. Both emerged in the early adoption phase, after initial experimentation but before company-wide scaling. These "early pathways" underscore the dynamic and evolving nature of GenAI adoption in IPCs.

4.1 Technological Challenges and Countermeasures of GenAI Adoption

Technical challenges in adopting GenAI frequently stem from the unique characteristics of foundation models, such as their non-deterministic behavior, variation across models, and potential for hallucinations (Goodfellow et al., 2020; Kingma & Welling, 2019). We illustrate the identified technological challenges and the respective countermeasures of IPCs in Table 2 below.

Table 2. Technological challenges and countermeasures of GenAI adoption in IPCs

IPC Challenges	Respective Countermeasures
T-C1: Model Hallucination. AI models may generate made up, inaccurate or misleading information, resulting in safety exposures, fatal product errors, reputational risk, and loss of trust. (C1, C6, C8)	**T-M1: Enterprise Grounding.** Hallucinations often stem from insufficient data and prompts. RAG and detail-driven prompt engineering improve accuracy and reliability. (C1, C6, C8)
T-C2: Non-Deterministic Nature & Reproducibility of Results. Prompt engineering builds on past attempts and failures. Sharing only current prompts in coding and engineering processes is ineffective. (C1, C2, C8, C9)	**T-M2: Standardized Testing Environments and Procedures.** Deploy prompt logging technology to capture prompt variations and support iterative testing and development in team settings. (C1, C2, C8)
T-C3: Multi-Model Interoperability. Prompt effectiveness varies across different models, slowing down model upgrade timeframes and introducing inconsistent response quality. (C2, C9)	**T-M3: Automated Regression Testing.** Use predefined evaluation tests (e.g., question-answer pairs, BLEU, ROUGE) to secure prompt performance across GenAI models. (C9, C10)

Model hallucinations (T-C1) often arise from a LLM-model's reliance on statistical patterns rather than factual validation, compounded by biases and gaps in its training data. In ambiguous contexts, the model fills in missing details with plausible yet incorrect information. This can manifest in different ways, such as fabricated text in LLMs, unrealistic visuals in image models, or distorted outputs in audio generation. Consequently, ensuring reliability and consistency in enterprise applications remains crucial, particularly in industries facing significant safety requirements or other regulations.

Tackling model hallucinations through specific countermeasures has shifted the focus from resource-intensive model fine-tuning (i.e., adapting a pretrained model using additional task-specific data) towards more cost-effective solutions, with companies recognizing Retrieval-Augmented Generation (RAG) (T-M1) as *"the tool of the hour"* for handling diverse use cases without deep customization (I20). While RAG enhances factual grounding by retrieving external data, it does not inherently address reasoning errors or deep contextual understanding, requiring additional layers of validation. One interviewee emphasized, *"RAG is a tool but won't do it alone"* (I06). Such an additional layer is prompt engineering, detailing the technique of designing the model input detail-driven and as a holistic task description. This combination of RAG and detail-driven prompt engineering has emerged as a practical and flexible approach to address and reduce model hallucinations, although it is not yet considered a miracle cure.

Furthermore, the non-deterministic blackbox nature of GenAI poses challenges for technical developers in terms of reproducibility and the transfer of existing work to other developers, as responses can vary even for the same prompt input (T-C2). Unlike traditional coding, where building upon the latest code base is standard practice, effective prompt engineering requires access to the full history of previous iterations, including failed or suboptimal prompts. Consequently, an immediate countermeasure includes the implementation of prompt logging (T-M2) to document variations in prompts and their performance.

Furthermore, rapid model updates by technology providers add complexity (T-C3), as companies need to balance the challenges of cost, quality, and latency. Not long ago, most enterprises were experimenting with only one (usually OpenAI's) or two models. Our recent discussions with enterprise leaders reveal a notable shift. Today, organizations are testing and, in some cases, deploying multiple models concurrently. This diversified approach enables them to tailor solutions based on performance, size, and costs, avoid vendor lock-in, and rapidly leverage emerging technological advancements. One interviewee noted, *"Fast upgrades are crucial but difficult"* in an industry where *"we think in years, GenAI in quarters"* (I10). To address these challenges, leading companies adopt rigorous automated regression testing (T-M3) to support the continuous modification and updating of models. For example, one organization *"automatically test[s] each LLM model with 200 predefined question-answer pairs"* to ensure consistent quality (I20). These predefined answers, created by internal experts, serve as reference points to assess factual accuracy, answer consistency across runs, and robustness against edge cases. By comparing the model's responses to these human benchmarks, teams can quickly gauge consistency and factual accuracy. When significant discrepancies arise, deeper human review follows.

4.2 Organizational Challenges and Countermeasures of GenAI Adoption

Within organizations, GenAI introduces both operational and cultural challenges. Table 3 below summarizes the key challenges and respective countermeasures.

Table 3. Organizational challenges and countermeasures of GenAI adoption in IPCs

IPC Challenges	Respective Countermeasures
O-C1: ROI Assessment. Difficulty in quantifying monetary gains on rather vague assumptions and linking AI-driven efficiencies to tangible financial outcomes. (C1, C4, C6, C10)	**O-M1: Minimum Viable KPI Set.** Instead of estimating monetary gains, use two KPIs for each use case: Adoption (Is it used?) and Performance (e.g., hours saved). (C4, C10)
O-C2: 'Hopium' & Usage Drop. High initial expectations lead to user frustration and a decline in usage if GenAI then cannot fulfil the raised expectations, leading to mistrust. (C1, C6)	**O-M2: Demystify Expectations.** Develop and deliver employee training to build a realistic understanding of GenAI's capabilities and limitations to foster a *'can-do'* culture. (C1, C6)
O-C3: Make vs. Buy Decision-Making. Unseen GenAI advancement speed makes in-house solutions quickly outdated, creating dilemmas about building or purchasing solutions. (C2, C4, C8)	**O-M3: Force Roadmap Disclosure.** Leverage buying power to compel tech providers to disclose their development roadmap to collaboratively mitigate development overlap. (C7, C9, C10)

Within industrial product companies, the adoption of GenAI presents both operational and cultural challenges that extend far beyond technical implementation. A primary hurdle is the assessment of return on investment (ROI) (O-C1). IPCs traditionally rely on ROI metrics to justify significant investments, yet GenAI's efficiency gains are difficult to capture in purely financial terms. One interviewee remarked, *"We will not see GenAI on the P&L, yet we will not invest in GenAI without conducting the necessary calculations backing investments of that size. Thus, we are in some kind of dilemma, whereas we don't want to get outpaced by our competitors, yet we don't have the resources to do all"* (I12). Another noted, *"Calculations are always estimates, that's for sure, but we really don't know whether we are in scope or completely out of scope"* (I05). To counter these uncertainties, many organizations are shifting focus from speculative monetary projections to concrete, measurable KPIs. Specifically, a minimal viable KPI set (O-M1) that evaluates both adoption (i.e., is the solution being used?) and performance (e.g., hours saved). The core idea is not to quantify perfect financial ROI but to enable consistent comparisons across use cases based on a shared operational baseline. This approach reframes success in operational terms, sidestepping the challenges inherent in financial quantification.

A related challenge is the phenomenon of "hopium" (O-C2), where high initial expectations lead to significant disillusionment. Early enthusiasm for GenAI often results in inflated promises that, when unmet, rapidly erode user trust. One organization reported that *"80% of the licenses we acquired are no longer used, because my people* *do not want to use it anymore. They really weren't happy with what it can do. It will be interesting, if these licenses will become active again, once the technology advances. Till then, we'll have to pay those licenses as well…"* (I05). In response, organizations are emphasizing the importance of demystifying expectations (O-M2) by investing in robust employee training programs. These programs are designed to build a realistic understanding of GenAI's capabilities and limitations, fostering a 'can-do' culture that encourages curiosity and gradual adoption rather than blind optimism.

Another critical decision-making challenge is the make versus buy dilemma (O-C3). The unprecedented pace of GenAI advancements renders in-house solutions vulnerable to rapid obsolescence, complicating decisions between custom development and purchasing pre-built vendor solutions. Many companies have observed that custom-built systems can quickly become outdated, forcing them to reconsider the risks associated with in-house development. To mitigate this risk, organizations are increasingly engaging in strategic partnerships with technology providers. By leveraging their buying power, companies are now able to force roadmap disclosure (O-M3), ensuring that vendors provide insight into future developments. This collaborative transparency not only helps avoid vendor lock-in but also enables companies to anticipate technological shifts, aligning their investments with a shared, forward-looking vision.

4.3 Environmental Challenges and Countermeasures of GenAI Adoption

Beyond internal and technological hurdles, IPCs must also navigate a complex external environment characterized by rapidly evolving regulatory demands and market dynamics. Table 4 illustrates core environmental challenges alongside corresponding countermeasures.

Table 4. Environmental challenges and countermeasures of GenAI adoption in IPCs

IPC Challenges	Respective Countermeasures
E-C1: Internal & External Compliance. Model outputs must adhere to IP, privacy, and copyright standards, which vary by jurisdiction and technology provider. (C1, C7, C8)	**E-M1: Content Validation Layer.** Define model output IP ownership in contracts and implement a content validation layer with clear supervisory rights and responsibilities. (C7, C9)
E-C2: Tech & Partner Lock-In. Single-provider dependence for GenAI can restrict flexibility and bind infrastructure to one vendor's capabilities, impacting adaptability. (C6, C8)	**E-M2: Model-Agnostic Architecture.** Separation of GenAIOps and models enables rapid switching between models and reduces dependencies on single providers. (C2, C7, C8)
E-C3: Novel AI Regulations. New legislation on AI (e.g., EU AI Act) adds complexity, necessitating compliance with diverse international regulatory requirements. (C1, C2, C10)	**E-M3: Compliance Assessment Framework.** Establish a standardized process that evaluates AI use cases for their compliance with regulations across all operational regions. (C10)

Externally, organizations face multifaceted compliance challenges. GenAI outputs must adhere to varying intellectual property, data privacy, and copyright standards that differ by jurisdiction and technology provider. A key concern for many firms is ensuring that prompts, information provided with the prompts (such as attached documents), and content generated under enterprise licenses remains the intellectual property of the company, not the model provider. In addition, outputs must comply with internal guidelines, particularly when exposed to external stakeholders. To mitigate these challenges, some companies implement a *"content validation layer"* (E-M1) that automatically screens model outputs for non-compliant elements such as threats, insults, or confidential information before they reach end users. In tandem, a compliance assessment framework (E-M3) is increasingly adopted to standardize evaluations of AI use cases, ensuring that all deployments consistently meet emerging regulatory demands (e.g., EU AI Act) across different regions.

A further environmental challenge arises from the risk of technological and partner lock-in. Relying on a single GenAI provider can restrict an organization's flexibility and tie its infrastructure to one vendor's evolving capabilities. In response, many organizations are shifting towards a model-agnostic architecture (E-M2). By decoupling GenAIOps from the underlying models, companies can rapidly switch between different providers, thereby *"avoid[ing] reliance on a single GenAI source"* (I10) and enhancing adaptability to market shifts. This approach not only safeguards operational resilience but also ensures that organizations remain agile in the face of both technological advancements and shifting vendor strategies.

In addition to regulatory and vendor-related challenges, environmental factors such as cost, latency, and throughput remain critical considerations. Not all models offer the same capabilities. Some provide higher quality but come at a greater cost. Others offer faster responses or can be deployed locally rather than through the cloud. As businesses scale their GenAI adoption, it becomes imperative to select models that strike a balance between performance quality and operational efficiency. One interviewee encapsulated this sentiment: *"It's more than just quality that counts, but also latency, throughput, and especially costs"* (I20). Ultimately, ICPs increasingly require the ability to choose from a range of models and align them with the specific use case demands.

5 Discussion

Industrial product companies face complex challenges when adopting GenAI that span technological, organizational, and environmental dimensions. Leveraging the TOE framework (Tornatzky & Fleischer, 1990), we expand these dimensions with GenAI-specific insights: non-determinism, hallucination risk, and model interoperability; prompt-engineering routines and lean KPI sets; emergent regulation and vendor-lock-in mitigation. We contrast these additions with classical DOI/TOE studies that describe incremental assimilation (Oliveira & Martins, 2011; Rogers, 1995) and early AI research that stressed data quality, model transparency, and workforce displacement (Berente et al., 2021; Dwivedi et al., 2024). Our nine challenge-countermeasure pairs thereby advance adoption theory in three ways: (1) they surface intangible micro-routines as a new organizational capability, (2) elevate vendor-agnostic architecture as an environment-shaping response that complements prior regulatory focus (Al-kfairy, 2025), and (3) lay an empirical foundation for a staged maturity view of GenAI adoption. Although some challenges may apply to other sectors, they are particularly pronounced in industrial product companies (Anderson et al., 2022) that must reconcile strict safety and IP demands with emerging GenAI regulation, making rigorous risk mitigation and partnership governance indispensable (Porter & Heppelmann, 2014; Wlcek et al., 2024).

While our findings offer targeted insights, they reflect the perspective of large, patent-active firms and thus are limited in transferability to SMEs. Although certain patterns may resonate more broadly, resource availability and governance structures imply that SMEs face distinct constraints. We invite future research to explore these differences and extend our results to a wider range of organizational contexts.

Altogether, our results highlight the deeply interconnected relationship between industrial product companies and AI technology providers. As these companies increasingly rely on close collaborative partnerships with tech vendors, they face the dual challenge of remaining both tone-setting and technology-agnostic. This dynamic calls for further investigation into effective collaboration and integration strategies that can help resolve the risks associated with vendor lock-in and ensure long-term flexibility.

Finally, we encourage scholars to develop a GenAI-adoption maturity model that maps the identified specific challenges and corresponding solutions to different successive stages of organizational GenAI adoption.

6 Conclusion

This paper offers a detailed analysis of the challenges and early pathways for adopting GenAI in industrial product companies. We conducted 22 expert interviews with representatives from 10 industrial product companies and their technology providers, many of which are recognized as GenAI leaders based on their patent portfolios. From these interviews, we derived a set of nine key challenges and their respective countermeasures. These challenges span technological, organizational, and environmental dimensions, covering issues such as model hallucinations, ROI assessment, unrealistic expectations, and regulatory as well as vendor dependency concerns. Our findings provide actionable insights for industrial product companies seeking to integrate GenAI into their operations while mitigating inherent risks. Future research should validate and extend our research and explore the interplay between the TOE dimensions in shaping the long-term success of GenAI adoption in these complex settings.

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